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# The Role of Personality, Memory, and Regulatory Focus for Human-Robot Interaction.

Arturo Cruz Maya

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# Le Rôle de la Personnalité, de la Mémoire et du Regulatory Focus sur l'Interaction Homme-Robot

Thèse de doctorat de l'Université Paris-Saclay  
préparée à ENSTA ParisTech

École doctorale n°573 : interfaces : approches interdisciplinaires,  
fondements, applications et innovation (Interfaces)  
Spécialité de doctorat: voir spécialités par l'ED

Thèse présentée et soutenue à Palaiseau, le 05 avril 2018, par

**Arturo Cruz Maya**

Composition du Jury :

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# Declaration of Authorship

I, Arturo CRUZ-MAYA, declare that this thesis titled, “The Role of Personality, Memory, and Regulatory Focus on Human-Robot Interaction” and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

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Date:

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*“The wise adapt themselves to circumstances, as water moulds itself to the pitcher.”*

Chinese proverb



Université Paris-Saclay

# *Resume*

ED: Interfaces

ENSTA ParisTech

## **Le Rôle de la Personnalité, de la Mémoire et de la Attention Réglementaire sur l'Interaction Humain-Robot**

par Arturo CRUZ-MAYA

**Mot clés:** Interaction Homme-Robot, robotic social, apprentissage machine, attention réglementaire, personnalité, adaptabilité de comportement du robot et personnalisation,

Dans le domaine de l'Interaction Homme-Robot, et plus particulièrement dans le domaine de la robotique sociale, les robots compagnons font de plus en plus partie de notre vie quotidienne et ont un grand potentiel pour aider les gens dans leurs activités quotidiennes, spécialement dans le cas d'une interaction "one to one". Ce scénario où les robots partagent le même environnement avec les humains et interagissent avec eux peut être bénéfique mais il peut aussi présenter des effets négatifs, comme générer un stress sur les utilisateurs humains, c'est aussi le cas de l'effet de la facilitation sociale, discuté au début de ce travail. Avoir des robots qui nous aident dans nos activités quotidiennes conduit à la nécessité de les doter de capacités sociales afin d'adapter leur comportement à leurs utilisateurs, leur environnement et leurs tâches. Néanmoins, comment réaliser cette adaptation reste un défi.

Afin de répondre à ces questions de recherche "Comment atteindre l'apprentissage de long term et l'adaptation pour l'interaction humaine-robot personnalisée?" et "Quel est le rôle de la personnalité, de la mémoire et de l'orientation réglementaire dans HRI?", nous proposons l'utilisation du modèle "Big 5 traits" de personnalité afin d'adapter le comportement du robot au profil des utilisateurs. De plus, notre système contient une implémentation du modèle d'émotions OCC et une mémoire de type épisodique, afin de générer un comportement naturel, capable de se souvenir des événements passés et de se comporter en conséquence. Nous présentons plusieurs études expérimentales, où nous testons notre système, et où nous analysons le lien



entre les traits de personnalité de l'utilisateur humain et le comportement du robot. La contrainte générée sur les utilisateurs a été mesurée en utilisant des capteurs externes tels qu'une caméra thermique et un capteur GSR. Notre système proposé s'est révélé efficace pour générer un comportement de robot adapté à la personnalité des utilisateurs. Nous avons trouvé quelques relations entre la personnalité, les préférences de l'utilisateur et la performance de la tâche, qui sont détaillées dans ce travail. Nos études ont montré que les personnes ayant un haut niveau de conscience ont une meilleure performance que les personnes peu consciencieuses. En outre, les personnes introverties étaient plus influencées pour effectuer une tâche que les personnes extraverties. En outre, nous avons observé une augmentation du stress de l'utilisateur, causée par un robot avec une voix semblable à une machine.

En plus de s'adapter aux préférences des utilisateurs, nous voulions que notre système soit capable de générer des comportements de robot capables de persuader efficacement leurs utilisateurs d'accomplir les tâches qu'ils doivent accomplir (prendre des médicaments, appeler des membres de la famille, etc.). Pour cette raison, nous proposons l'utilisation de la théorie Regulatory Focus, qui se concentre sur les inclinations que les gens ont lorsqu'ils prennent des décisions, et comment augmenter la motivation des gens à atteindre un objectif. Nous avons mené plusieurs expériences afin de valider cette théorie dans le contexte de l'interaction homme-robot. Nos résultats montrent que les comportements de robot basés sur la théorie de la focalisation réglementaire, y compris les gestes corporels et la vitesse de la parole, sont efficaces pour persuader les utilisateurs d'accomplir une tâche. Nous avons également constaté une augmentation du stress chez les utilisateurs lorsque le robot ne correspondait pas à l'état réglementaire de l'utilisateur.

Nous concluons que les sujets étudiés dans cette thèse: personnalité, mémoire et attention réglementaire, doivent être inclus dans la conception des comportements des robots, afin d'avoir des robots plus efficaces sur les tâches persuasives, et comportements moins stressant pour leurs utilisateurs .

Université Paris-Saclay

# *Abstract*

ED: Interfaces

ENSTA ParisTech

Doctor of Philosophy

## **The Role of Personality, Memory, and Regulatory Focus on Human-Robot Interaction**

by Arturo CRUZ-MAYA

**Keywords:** human-robot interaction, social robotics, machine learning, regulatory focus, personality, robot behavior adaptation and customization

In the domain of Human-Robot Interaction, and more specifically in the social robotics field, companion robots are more and more part of our daily lives and they have a great potential for helping people in their daily activities, especially in tasks that need one-on-one interaction. This scenario where robots are sharing the same environment with the humans and interact with them can be beneficial but it can also present some negative effects like generating stress on the human users, this is also the case of the social facilitation effect, discussed at the beginning of this work. Having robots helping us with our daily activities leads to the need of endowing them with social capabilities in order to adapt their behavior to their users, environment, and tasks. Nevertheless, how to achieve this adaptation remains a challenge.

In order to address these research questions, "How to achieve lifelong learning and adaptation for personalized Human-Robot Interaction?" and "What is the role of personality, memory, and regulatory focus in HRI?", we propose the use of the Big 5 personality traits model in order to adapt the robot's behavior to the profile of the users. Moreover, our system contains an implementation of the OCC Model, and an Episodic-like Memory, in order to generate a natural behavior, being capable of remembering past events and behaving accordingly. We present several experimental studies, where we test our system, and where we analyze the link between the human user's personality traits and robot's behavior. The generated stress on the users

was measured by using external sensors such as a thermal camera and a GSR sensor. Our proposed system showed to be effective in generating a robot behavior adapted to users personality. We found some relations between personality, user preferences and task performance, which are detailed in this work. Our studies showed that people with high conscientiousness have greater task performance than people with low conscientiousness. Also, that introverted people were more influenced to perform a task than extroverted people. Also, we observed an increase on user stress, caused by a robot with a machine-like voice.

In addition to adapting to the users preferences, we wanted our system to be able to generate robot behaviors capable of persuading effectively their users in achieving the tasks they need to do (i.e. taking medication, calling family members, etc). For this reason, we propose the use of the Regulatory Focus theory, which concentrate on the inclinations that people have when taking decisions, and how to increase the motivation on people to achieve an objective. We conducted several experiments in order to validate this theory in the context of human-robot interaction. Our results show that robot behaviors based on the Regulatory Focus Theory, including body gestures and speech speed, are effective in persuading users to accomplish a task. We also found an increase on user stress when the robot did not match the user Chronic Regulatory State.

We conclude that the topics investigated in this thesis: Personality, Memory and Regulatory Focus, have to be included in the design of robot behaviors, in order to have more efficient robots on persuasive tasks, and less stressing behaviors to their users.

Université Paris-Saclay

# *Resumen*

ED: Interfaces

ENSTA ParisTech

## **El Role de la Personalidad, la Memoria, y la Atencion Reguladora sobre la Interacción Humano Robot**

por Arturo CRUZ-MAYA

**Palabras Clave:** Interacción Humano-Robot, robótica social, aprendizaje máquina, atención regulatoria, personalidad, adaptación de comportamiento de robots y personalización

En el dominio de la Interacción Humano-Robot (IHR), y más específicamente en el campo de Robótica Social, los robots de compañía cada vez más forman parte de nuestra vida diaria y tienen un gran potencial para ayudar a la gente en sus actividades cotidianas, específicamente en tareas que necesitan interacciones uno a uno. Este escenario donde robots comparten el mismo entorno con humanos e interactúan con ellos puede ser benéfico pero también puede presentar algunos efectos negativos como generar estrés sobre los usuarios humanos, este es el caso del efecto de facilitación social, abordado al inicio de este trabajo. Tener robots ayudándonos en nuestras actividades diarias genera la necesidad de dotarlos con capacidades sociales con el fin de adaptar su comportamiento a sus usuarios, entorno, y tareas. Sin embargo, como lograr dicha adaptación sigue siendo un reto.

Con el fin de responder las preguntas de investigación, "¿Cómo lograr un aprendizaje y adaptabilidad de tiempo de vida para una interacción Humano-Robot personalizada?" y "¿Cuál es el rol de la personalidad, la memoria, y la atención regulada en (IHR)?", nosotros proponemos el uso del modelo de tipos de personalidad "Big 5" con el fin de adaptar el comportamiento del robot a el perfil de los usuarios. Además, nuestro sistema contiene una implementación del modelo de emociones "OCC", y una Memoria tipo Episódica, con el fin de generar un comportamiento natural, capaz de recordar eventos pasados y comportarse de acuerdo a ellos. Presentamos diversos estudios experimentales, donde probamos nuestro sistema y donde analizamos las

relaciones entre los tipos de personalidad de usuarios humanos y el comportamiento del robot. El estrés generado en los usuarios fué medido usando sensores externos tales como una cámara térmica y un sensor GSR. Nuestro sistema propuesto mostró ser efectivo en generar un comportamiento adaptado a la personalidad de los usuarios. Encontramos algunas relaciones entre personalidad, preferencias de usuario, y rendimiento en tareas, las cuales son detalladas en este trabajo. Nuestros estudios muestran que personas con alto nivel de conscientividad tienen un mayor rendimiento en tareas que personas con bajo nivel de conscientividad. Además, muestran que personas introvertidas fueron más influenciadas para realizar una tarea que personas extrovertidas. Así mismo, observamos un incremento de estrés en los usuarios, causados por un robot con voz robótica.

Además de adaptarse a las preferencias de los usuarios, nosotros quisimos que nuestro sistema pudiera generar comportamientos de robot capaces de persuadir efectivamente a sus usuarios en tareas que ellos necesiten realizar (i.e. tomar medicamentos, llamar a familiares, etc). Por esta razón, proponemos el uso de la Teoría Atención Regulada, la cual se concentra en la inclinación de las personas en la toma de decisiones, y en cómo incrementar la motivación de las personas en lograr un objetivo. Conducimos varios experimentos con el fin de validar esta teoría en el contexto de la Interacción Humano-Robot. Nuestros resultados muestran que los comportamientos del robot basados en la teoría de la Atención Regulada, incluyendo posturas corporales y la velocidad de la voz, son efectivas en persuadir usuarios en realizar una tarea. Además encontramos un incremento de estrés en los usuarios cuando el robot no coincidía con su estado crónico de atención regulada.

Concluimos que los temas investigados en esta tesis, es decir: Personalidad, Memoria, Atención Regulada, tienen que ser incluidas en el diseño de comportamientos de robot, con el objetivo de tener robots más eficientes en tareas persuasivas, y comportamientos menos estresantes para sus usuarios.

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# List of Abbreviations

|                 |  |
|-----------------|--|
| <b>ANOVA</b>    | <b>AN</b> alysis <b>O</b> of <b>V</b> ariance  |
| <b>ASR</b>      | <b>A</b> utomatic <b>S</b> peech <b>R</b> ecognition   |
| <b>CONACYT</b>  | <b>C</b> onsejo Nacional (de) <b>C</b> iencia <b>Y</b> <b>T</b> ecnología  |
| <b>EM</b>       | <b>E</b> pisodic <b>M</b> emory  |
| <b>EM-ART</b>   | <b>E</b> pisodic <b>M</b> emory - <b>A</b> Adaptive <b>R</b> esonance <b>T</b> heory   |
| <b>ENRICHME</b> | <b>E</b> Nnabling <b>R</b> obot (and assisted living environment for)<br><b>I</b> ndependent <b>C</b> are (and) <b>H</b> ealth <b>M</b> onitoring (of the) <b>E</b> lderly |
| <b>GSR</b>      | <b>G</b> alvanic <b>S</b> kin <b>R</b> esponse   |
| <b>HRI</b>      | <b>H</b> uman <b>R</b> obot <b>I</b> nteraction  |
| <b>HTML</b>     | <b>H</b> yper <b>T</b> ext <b>M</b> arkup <b>L</b> anguage   |
| <b>HV</b>       | <b>H</b> uman <b>V</b> oice  |
| <b>OCC</b>      | <b>O</b> rthony <b>C</b> laire <b>C</b> ollins (Model)   |
| <b>RGB</b>      | <b>R</b> ed <b>G</b> reen <b>B</b> lue   |
| <b>RGB-D</b>    | <b>R</b> ed <b>G</b> reen <b>B</b> lue <b>D</b> epth   |
| <b>RFT</b>      | <b>R</b> egulatory <b>F</b> ocus <b>T</b> heory  |
| <b>SD</b>       | <b>S</b> tandar <b>D</b> eviation  |
| <b>SV</b>       | <b>S</b> ynthesized <b>V</b> oice  |
| <b>TTS</b>      | <b>T</b> ext <b>T</b> o <b>S</b> peech   |



*Dedicated to my family*



# Chapter 1

## Introduction

### 1.1 Context

In the domain of Human-Robot Interaction, and more specifically in the social robotics field, companion robots have a great potential for helping people in their daily activities, especially in tasks that need one-on-one interaction, as is the case of elderly people or children. Social robots will be more and more part of our daily lives in the next years, and having long-term interactions can have both positive and negative effects on their users. Some negative effects can be generating stress on the users, or the users can lose interest on the robots and do not use them anymore. Having robots helping us with our daily activities lead to the need of endowing them with social capabilities in order to adapt their behavior to their users, environment, and tasks. Nevertheless, how to achieve this adaptation remains a challenge.

Works in social psychology have shown that there exist inter-individual differences. These differences are part of the personality. The literature shows that people with similar personality have similar preferences (Byrne, Griffitt, and Stefaniak, 1967), (Winch, Ktsanes, and Ktsanes, 1954). Therefore, this can be used to generate robot behaviors based on users' personality.

One of the main purposes of companion robots is to use them to remind their users about the tasks they have to do, as embodied agents could be more persuasive than not physical agents. The interaction requires robots to adapt to the person with respect to their preferences and therefore to take into consideration the inter-individual and intra-individual differences. A theory proposed in the field of social psychology, called Regulatory Focus Theory (Crowe and Higgins, 1997), states that people have one of the two different inclinations for decision making: promotion focus or prevention focus. These inclinations can be used to increase people's motivation to perform a certain task. Then, the inclusion of this theory in generating robot behaviors for social robots seems appropriate.



A pioneering work on Social Robotics was developed by Cynthia Breazeal (Breazeal, 2003). She developed a theoretical framework for robot behaviors, based on ethological and emotional models, and implemented it on a robot called "Kismet". The emotional components of such framework were: a precipitating event, an affective appraisal, a characteristic expression (face, voice, posture) of the robot, and action tendencies that motivate a behavioral response. The robot recognized affective intent through tone of voice, inspired on the findings of the developmental psycholinguistic community. This robot allowed to investigate the role of emotion and expressive behavior in regulating social interaction between humans and expressive anthropomorphic robots. The robot's facial expression allowed to reflect the internal state of its emotional system. Also, this method allowed the users to have immediate feedback on how their behavior influenced the robot's internal state by watching the robot behavior. Nevertheless, this work did not implement a long-term adaptive behavior for Human-Robot Interaction.

Another robot that made a strong impact in the Social Robotics community, was developed by Takanori Shabata (Schröder and Trouvain, 2003). This robot was called "Paro", which had an animal form, a baby seal. The pet robot had visual, auditory, and tactile sensors, and it targeted a different audience than industrial robots, one that is not so dependent on objective measures, as accuracy and speed. The main contribution of this robot was the demonstration that an engaging interaction can occur through by non-verbal communication between human and robot through physical interaction. Also, this robot proved to be effective in assisting activity of elderly people at health service facilities, where the moods of elderly people were improved by their interaction with "Paro" robots. However, this approach had numerous disadvantages, such as the lack of speech generation, or an anthropomorphic body, which limits the behavior of the robot. Moreover, it does not have a long-term memory and therefore it can not remember past interactions with its users, and it can not generate adaptive behavior.

An important project realized in the field of HRI, is the Adaptive Strategies for Sustainable Long-Term Social Interaction (ALIZ-E) project<sup>1</sup>, which is a multi-partner initiative focused on long-term adaptive social interaction between robots and child users built up through sessions of long periods of days. They found evidence that robots received more attention than on-screen avatars, which opens possibilities for education and social interaction.

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<sup>1</sup><http://www.aliz-e.org>

Also, they found that less complex but more robust and flexible behaviors are the ones that produce better results with the users (Belpaeme et al., 2012).

Some work in social robotics has taken advantage of the differences of user personality. Woods et al. (Woods et al., 2005) proposed to adapt the behavior of a robot to the users based on their personality. Tatsuhiro Kishi and his colleagues, showed that synthesis and recognition of emotions are important in order to have robots more appealing to humans and to be perceived as more useful and expressive (Kishi et al., 2013).

Other works in the of field Human-Robot Interaction, have showed the importance of other features for social robots. The use of long-term memory is important to keep information about past events to use during new events (Dodd and Gutierrez, 2005). They designed and created an episodic memory system for a cognitive robot, which interfaced with an emotion system to retrieve the most emotionally salient episode. This work showed the plausibility to incorporate an emotion system in a memory system for generating intelligent robot behaviors. Nevertheless, this work can be enriched with the use of social psychology theories for generating appropriate behaviors.

Social robots need to be able to persuade and motivate their users. For this reason, persuasiveness of robots have been studied by (Ham et al., 2011). They studied the combined and individual contribution of gazing and gestures to the persuasiveness of a storytelling robot. They found that gaze increases robot persuasiveness, while gestures alone decreases it. Combining gaze and gesture has a greater increase on robot persuasiveness.

To the best of our knowledge, the use of user personality in combination with an emotion and memory system to generate an adaptive behavior for motivating people to achieve a task while minimizing their stress has not been investigated thoroughly. Moreover, the increase of user motivation to perform a task, by a robot using a behavior based on the Regulatory Focus Theory has not been studied before.

This thesis focuses on the role of memory, personality, and regulatory focus in Human Robot interaction. We addressed these aspects in several experimental studies.

## 1.2 Proposed Work

The focus of this thesis is novel and it was not fully addressed in the literature.

The contributions are as follows:

Chapter 2. We present an extended literature review based on research work found in social sciences literature for Human-Human interaction, in order to address these research question, "How to achieve lifelong learning and adaptation for personalized Human-Robot Interaction?" and "What is the role of personality, memory, and regulatory focus in Human-Robot Interaction (HRI)?". The theories covered in this review include: Emotion Theories; Cognitive and Non-cognitive Behavior Theories; Personality and Regulatory Focus. Moreover, a small description of memory types including Episodic Memory is also presented.

Chapter 3. We present a study of a social effect called "Social Facilitation" (Zajonc et al., 1965) in Human-Robot Interaction in a game-like scenario, we implemented on our robot, an adaptation of the OCC Model (Ortony, Clore, and Collins, 1990) and an Episodic-Like Memory System (Leconte, Ferland, and Michaud, 2014). This work was published in (Cruz-Maya, Ferland, and Tapus, 2015). Knowing that this social effect happens in Human-Human Interaction, we tested our implementation on its effect in a Human-Robot Interaction experiment. We adapted a Psychological Model for Emotions, knowing that a robot behavior based on the implementation of psychological models has proved to be capable of generating believable natural behaviors (Breazeal, 2003). We opted to use the OCC Model due to it being a cognitive model. It makes a reasoning on past events and the current context to generate the emotions. As our objective is to develop a framework capable of adapting to the users in the long-term, we decided to include the use of an Episodic-Like Memory system on our framework, because this is a long-term memory that is in charge of retrieving the personal experiences events (Tulving, 2002), and it had been implemented on an autonomous robot (Leconte, Ferland, and Michaud, 2014). We integrated the OCC model and the Episodic-Like Memory system in a framework and implemented it on a humanoid robot (Nao Robot) with the purpose of allowing a natural Human-Robot interaction.

Our framework showed to be effective for generating a natural human-robot in a short-term interaction. Nevertheless, this approach depends on past events, and we did not have a way to model the robot behavior when there are no previous interactions with the user. For this reason, we formulate the hypothesis, based on (Allbeck and Badler, 2002) and (Reisenzein and Weber, 2009), that we should have a pattern of people behavior for generating a robot behavior when there are no previous interactions.

Chapter 4. We present a study on the relation between user's personality

and robot reminders on a set of nine different conditions. This relation is of high importance to us in order to obtain information about preferences and performance of people with different personalities. Because robots are and will be more and more part of our everyday lives, and they will sometimes have to interrupt us during our daily tasks, we need to find the best approach to do it and investigate if the personality of the user is an important factor. To the best of our knowledge, there are no studies about personality and robot reminders. We opted for the use of the most accepted personality trait model in the contemporary literature, which is the Big 5 personality trait (Norman, 1963) (Digman, 1996). We study the effect on performance with respect to three interaction parameters (i.e., distance, height, and smile) in relation with two traits of personality of the user (i.e., conscientiousness and extroversion). The scenario is an office-like environment where the robot, a Meka robot (Meka Robotics - Google X), provides reminders to the participant. We published the work of this chapter in (Cruz-Maya and Tapus, 2016a).

Chapter 5. We analyzed the relation between the robot's embodiment, and machine voice and user stress. We compared them with the use of a tablet computer and human voice. We also analyzed the relation of the user's personality and four conditions combining the voice and embodiment. We developed a multimedia presentation in HTML and javascript based on the guide for Multimedia Learning proposed by (Mayer, 2014a), which was presented on a Kompai robot and a tablet computer to different groups of users. The robot used in our experiments was a Kompai robot, a robot developed by RoboSoft robotics company (currently Kompai robotics) as a home care system. It included a tablet PC where the multimedia information was presented (this computer was also used as tablet for some groups of participants). The synthesized voice was generated with the MaryTTS (Schröder and Trouvain, 2003) software using a French male voice. The human voice was recorded by a native French male person. This work was published in (Cruz-Maya and Tapus, 2016b).

Our findings on user preferences matched the personality theories, which state that people with the same personality have similar preferences. Nevertheless, there exists two theories that seem to be opposite of each other. For this reason, we think that a better approach would be letting the robot adapt to the personality of user based on the interaction with the user.

Chapter 6. We propose a framework that includes an Adapted Episodic Memory-like system, which is extended to an emotion system based on the

OCC Model to update the intensity of the memories of past interactions with respect to the user's feedback. This framework is not only aimed to remember the preferences of specific users, but also to generate behaviors for new users based on their personalities. This system can generate both user-specific and personality-based behaviors, using the interactions with different users instead of preset information. We describe our proposed framework for an adaptive robot behavior, as well as an experiment divided in two parts. In the first part, the model of the robot's behavior is created. A group of participants interacts with the robot three times, on different days each time, and they specify their preferences for three parameters defining the robot's behavior in a close interaction (as shown in Fig. 6.1). The preferences are saved individually for each user and also grouped by personality and gender. In the second part of the experiment, the current state of the robot's memory is used to generate the saved behavior to other group of participants with respect to their personality and gender.

The use of personality traits to create our model, performed well to predict user preferences. Nevertheless, we did not find evidence that it helps to increase motivation and performance of people when they are performing a task. For this reason, we opted to use an alternative theory, called Regulatory Focus, which is more linked with performance.

Chapter 7. We propose the use of motivation based on the Regulatory Focus theory (Crowe and Higgins, 1997), in order to match the Chronic Regulatory State of the participants with a regulatory oriented strategy used by a robot. The Regulatory Focus theory states that people have one of the two different inclinations for decision making: promotion focus or prevention focus. Promotion focus is related to risk situations, while prevention focus is related to security. We investigate the effect of regulatory focus induced by a robot to a group of participants, testing the match and mismatch of Chronic Regulatory State of the participants and the Regulatory oriented strategy used by a robot. We designed an experiment where a robot, Tiago (Pal Robotics), gave instructions to complete a Stroop Test to a group of participants. The participants were divided in groups with respect to their score on a test of Regulatory Focus. The robot had 3 conditions, in the first and control condition, the robot did not include any regulatory strategy. In the second condition the robot gave instructions that included a Promotion oriented strategy, while for the third condition it included a Prevention oriented strategy. We found that a matching between the strategy of the robot and the

Chronic Regulatory State of the participants, lead to an increase on user performance. This work was published in (Cruz-Maya, Agrigoroaie, and Tapus, 2017).

Chapter 8. We studied the use of different robot behaviors based on Regulatory Focus Theory to increase user performance. According to Higgins, an increase of persuasiveness, can be achieved by non-verbal cues such as body gestures and the speed of the speech. We propose using different gestures and varying the speed of the speech, in order to minimize the user's stress and increase user's performance. We present an analysis of three different robot behaviors: robot control condition, robot Promotion based behavior, and robot Prevention based behavior. The behavior of the robot (Pepper robot) was presented to the user in a negotiation scenario. Also, participants were divided in groups based on their Regulatory States: in Promotion and Prevention groups, respectively. In the negotiation game scenario, the participants played the role of the seller, and the robot played the role of the buyer, where the robot followed a cooperative-competitive strategy. A publication about this work will appear (at the moment of writing this thesis) in (Cruz-Maya and Tapus, 2018).

Chapter 9. We present the conclusions and contributions of this work. Also we present the limitations and future directions.



## Chapter 2

# Theoretical Foundations

In order to address these research question, "How to achieve lifelong learning and adaptation for personalized Human-Robot Interaction?" and "What is the role of personality, memory, and regulatory focus in HRI?", an extended literature review based on research works found in social sciences literature for Human-Human interaction was conducted.

In this chapter, the theories on which this work is based are presented. These theories are of great importance and help us understand the human behavior. Our goal is to integrate these different paradigms in a robotic system, which is intended to interact with people in their everyday life.

We intend to create a natural interaction between humans and robots. The literature shows that robots equipped with a mechanism capable of generating and expressing emotions are rated as more engaging than robots that do not express emotions (Breazeal, 2003). Therefore, our first focus is emotion based behavior approach.

The models describing the emotions can be divided in two broad categories: Cognitive and Non-Cognitive emotions. For this reason, we begin by briefly explaining the main Emotion Theories in section 2.1, describing the Non-Cognitive Theories (section 2.1.1) and the Cognitive Theories (section 2.1.2), arguing that the Cognitive approach is more suitable for the purpose of this work. We continue with the description of the cognitive emotion model used (OCC Model), which is described in section 2.1.2, as well as the reason why we chose this specific model.

The cognitive model, is by definition, linked to a memory system. The memory encodes the events generating the emotions, which can be used to retrieve events from the past and generate the emotions at another time (Bruning, Schraw, and Ronning, 1999). Unfortunately, the OCC model does not specify anything about the memory. In order to include a memory in our system, we decided to use an Episodic-Like Memory system. In section 2.2, a brief description of a categorization of the memory systems is presented, and



in section 2.2, the Episodic Memory is depicted so as to explain how it works and why we used this memory in the proposed framework.

Nevertheless, the use of emotions and a memory system to model a robot behavior was not enough for us to create a personalized behavior. We faced the problem of how the robot should behave with new users, as it will not have memories from past interactions. We needed an approach to generate a default behavior, which would be the most suitable possible for all the users.

For those reasons, we decided to include a theory about personality behavior. In section 2.3 the known behavior theories, which have been proposed in the field of psychology are examined and presented. The Personality Theories are also presented in section 2.3.1. As there are many models in the literature about personality traits, the Big Five Personality Trait (section 2.3.1) was chosen because this theory is the more accepted in the contemporary literature. These topics are presented in detail and we argue that these theories and models are the most suitable for our work.

Another important aspect in our work is to increase motivation and performance of people when they are performing a task. We realized some experiments analyzing the personality traits using the Big 5 and user performance, but we did not find satisfactory results on this topic (we did for user preferences). Because of that, we examined many motivational theories and we inspired ourselves from an approach called Regulatory Focus Theory, explained in section 2.3.2. This can also be used to persuade people and can be of great help for companion robots to motivate their users to do activities for their benefit, such as physical exercise, taking medication, etc.

In section 2.4, the conclusion of the various theories and our choices covered in this chapter are presented.

## 2.1 Emotion Theories

At the beginning of our work, we focused on the use of synthesized emotions on a robot, in order to generate believable behaviors, with the purpose of having robots that are more engaging for the users. Nevertheless, for many years, psychologists tried to decide what are the emotions and what are their roles in an interaction, and these are still open questions until today. Many theories of emotions have been proposed (for a review, see Moors, 2009), which can be grouped in two categories: cognitive theories and non-cognitive theories. We start by presenting a short review of these categories.

### 2.1.1 Non-Cognitive Theories

Non-cognitive theories were first developed by two authors independently, William James and Carl Lange (James, 1884, Lange, 1885). They stated that an emotional experience is a mental state of a bodily response to an external stimulus (i.e. "we feel afraid because our body trembles because of a bear"). William James considered the emotion as the feeling of the bodily changes that follow the perception of an exciting fact (see Fig. 2.1). Lange argued that if we remove all the bodily sensations, there is nothing left of the emotion, only pure rational knowledge of the event that caused the emotion.

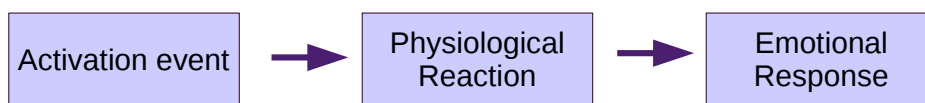


FIGURE 2.1: James-Lange Theory

Later, Paul Ekman developed what is considered the standard of the Non-Cognitive process of emotions. Ekman adopted an evolutionary point of view, where a group of six emotions (i.e., happiness, sadness, fear, anger, disgust, and surprise) that he called "basic emotions" (Ekman, 1992), evolved in response to ecological conditions, and each emotion is linked with a specific neurological circuit. Accordingly to Ekman, the characteristics, which distinguish these basic emotions are: distinctive universal signals, distinctive physiology, quick onset, automatic appraisal, brief duration, unbidden occurrence, distinctive thoughts, and distinctive subjective experience. Also, Ekman stated that each of these basic emotion can be distinguished by different facial expressions (Ekman and Oster, 1979).

The Ekman model of emotions has been widely used in facial emotion recognition (Ekman and Friesen, 2003 Kobayashi and Hara, 1992), also, it has been used to generate facial expressions of emotions on robots ( Hashimoto et al., 2006 Miwa et al., 2002).

Many implementations on robotics have been based on non-cognitive models to generate emotions on robots. Some examples are: Felix, a LEGO robot that displays different emotional expressions in response to physical stimulation, which could express anger, sadness, fear, happiness and surprise (Cañamero and Fredslund, 2001). Kismet (Breazeal, 2003), which is a robot whose emotional components are: a precipitating event, an affective appraisal, a characteristic expression (face, voice, posture) and action tendencies that motivate a behavioral response. Also its model include a mapping of

emotional categories to arousal, valence and stance dimensions. Other robot based on a Non-cognitive model approach to generate emotions, is the robot Probo, which is a animal-like robot with focus on non-verbal communication (Saldien et al., 2010)

### 2.1.2 Cognitive Theories

The precursors of this theories are Walter Cannon and Philip Bard, state that emotions are cognitive processes. Besides they state that emotions and physiological reactions are felt at the same time. Their theory emerged as a critic of the James-Lange Theory (Cannon, 1927) which today is known as the Cannon-Bard Theory (see Fig. 2.2).

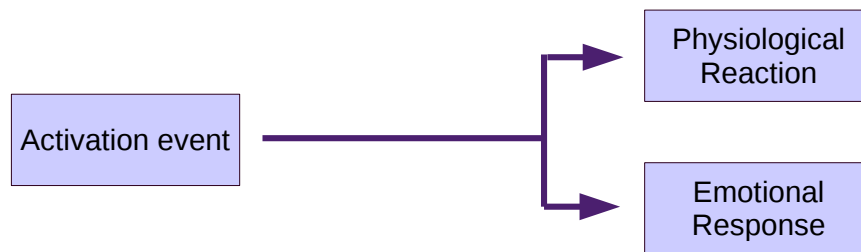


FIGURE 2.2: Cannon-Bard Theory

Cannon (Cannon, 1928) proposed that emotions can be experienced even when physiological reactions are not present, and also that different emotions can present similar reactions (like increasing heart-beat in response to fear or anger).

Another cognitive theory is the Schachter-Singer Theory (also known as the two-factor theory) (Schachter and Singer, 1962). This theory states that physiological arousal occurs first, but these reactions are often similar to different emotions. Moreover, they specify that such reactions should be cognitively labeled as a specific emotion.

Richard Lazarus proposed the Cognitive-Mediational Theory (Lazarus, 1991), where the appraisal mediates between the stimulus and the emotional response (see Fig. 2.3). This appraisal is the interpretation we give to a particular situation, it can be good or bad, and can be different in different people. Also, Lazarus, distinguishes two types of appraisal: 1) primary appraisal, which tries to give a meaning to an event, and 2) secondary appraisal, which is the ability to deal with the consequences of an event.

A contemporary theory is the one of Antonio Damasio, called the somatic marker hypothesis (Damasio, Everitt, and Bishop, 1996). He states that the

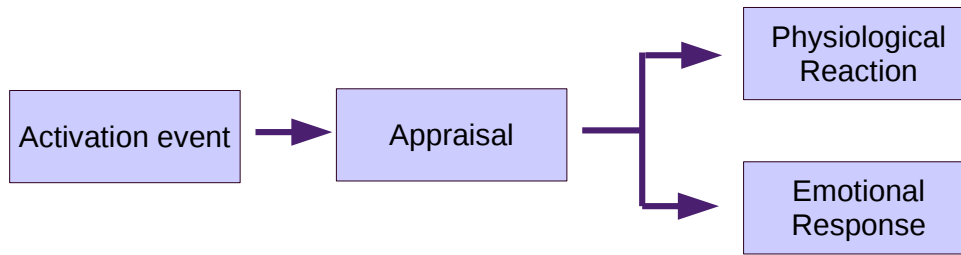


FIGURE 2.3: Cognitive-Mediational Theory

emotion process starts with the perception of a stimulus, which provokes a cognitive evaluation, and this generates a bodily response, followed by a perception of a certain body activity (see Fig. 2.4). Furthermore, Damasio proposes a link between the cognitive evaluation and the perception of activity in the body, called as-if-loop (as if the body was active).

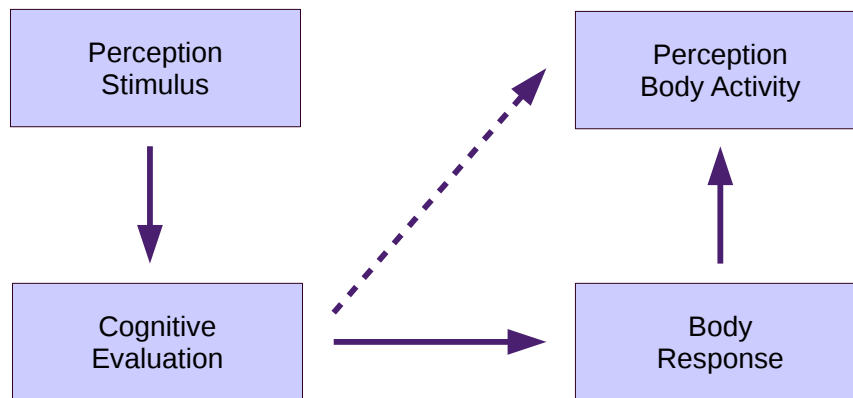


FIGURE 2.4: Damasio's Theory

Cognitive theories have been also adopted to generate emotions on robots by several researchers. Some examples are the work proposed by (Gadanh and Hallam, 2001), which consists of an adaptive model of emotions using a Q-Learning algorithm combined with an associative memory model using neural networks. Other work based on a cognitive approach was done by (Fellous, 2004) that proposes the use of neuromodulation to understand how emotions arise, are maintained, and interact with other aspects of behavior and cognitive processing. Also, there is a work on affective appraisal versus cognitive evaluation in social emotions (Castelfranchi, 2000), which states that human emotions are complex and rich mental states, and not just simple human mechanisms.

## OCC Model

After reviewing the literature about the cognitive and non-cognitive models, we decided to use a cognitive based approach, so as to have a robot behavior based on a cognitive evaluation of the situations, and generate the appropriate emotions. Among these types of cognitive models, we found the OCC Model to be most suitable, as it has a wide range of emotions and it have been partially implemented already on virtual characters and some robots.

The OCC Model is a cognitive appraisal theory of emotions developed by Ortony, Claire, and Collins (Ortony, Clore, and Collins, 1990). It was created with the objective to be a model for computational implementations, giving to Artificial Intelligences (AI) the capacity to reason about emotions. Nevertheless, it has been widely used to synthesize emotions for virtual animated characters (André et al., 2000b). Also, it has been partially implemented in some robot systems (Kröse et al., 2003).

This model contains twenty two emotion, divided in three categories. Accordingly with this theory, the aspect of an object can elicit emotions of attraction: love or hate, depending if we like or dislike such object. The action of an agent can generate emotions of attribution (i.e. pride or shame) depending on the agent doing the action. The consequences of an event, if the consequences are for others, can elicit emotions of fortune of others(i.e. happiness for the other or resentment), depending if the consequences are desirable or undesirable. If the consequences of an event are for itself, we can experience emotions of well-being (i.e. joy, distress, hope, or fear) depending on the relevance of the prospects. Also, if the fear is confirmed, it can elicit the emotion of panic, or if the fear is unconfirmed, it can elicit relief, which are prospect based emotions. In the same way if the hope is confirmed or not, it can elicit satisfaction or disappointment. Also, if joy and distress are combined with pride/shame and admiration/reproach, other emotions are elicited: gratification/remorse, and gratitude/anger, these are compound emotions between the well being and the attribution emotions. In Fig. 2.5, we can see the structure of the OCC Model.

This model states that emotions are generated based on cognitive evaluations to three eliciting conditions:

- Aspect of objects
- Actions of agents
- Consequences of events

Each eliciting condition have a group of local variables, and all of them share a group of global variables, which combined gives an emotion potential. This emotion potential, needs to surpass a threshold in order to generate the intensity of the emotion.

The global variables are:

- *Sense\_of\_Reality*: The degree in which an object, action of agent or an event seems to be real for the agent.
- *Proximity*: Psychological and physical proximity of the condition (object, action, or event).
- *Unexpectedness*: Difference between the condition and the agent's expectations.
- *Arousal*: Degree of how much the agent is alert.

The local variables for the Aspect of Objects are:

- *Appeal*: This can be seen as the degree of how much an agent like certain object, this can be set-up in the agent's preferences.
- *Familiarity*: It refers to the degree of how familiar is an object to the agent, this variable can be obtained from the memory of the agent.

The local variables for the Actions of Agents are:

- *Praiseworthiness*: It refers to the degree of how much an action worth for the agent.
- *Strength\_of\_Cognitive\_Unit*: This variable refers to the degree of how much the agent's preferences match the action.
- *Expectation\_Deviation*: It is how much the action is different than the standards of the agent.

The local variables for the Consequence of Events are:

- *Desirability*: This variable refers to the degree of how much the consequence of an event (positive and negative) is desired for the agent.
- *Likelihood*: It is the expected likelihood to obtain a certain consequence of an event.

- *Effort*: This is the effort put on the realization of the event.

Combining the local variables with the global variables gives us the intensity of the emotions, unfortunately, the authors of this theory do not explain in detail how to achieve this. Rosalind Picard in her book *Affective Computing* (Picard and Picard, 1997), proposes some rules to synthesize the emotion of Joy. We inspired our work from her work to synthesize the emotions on the robots.

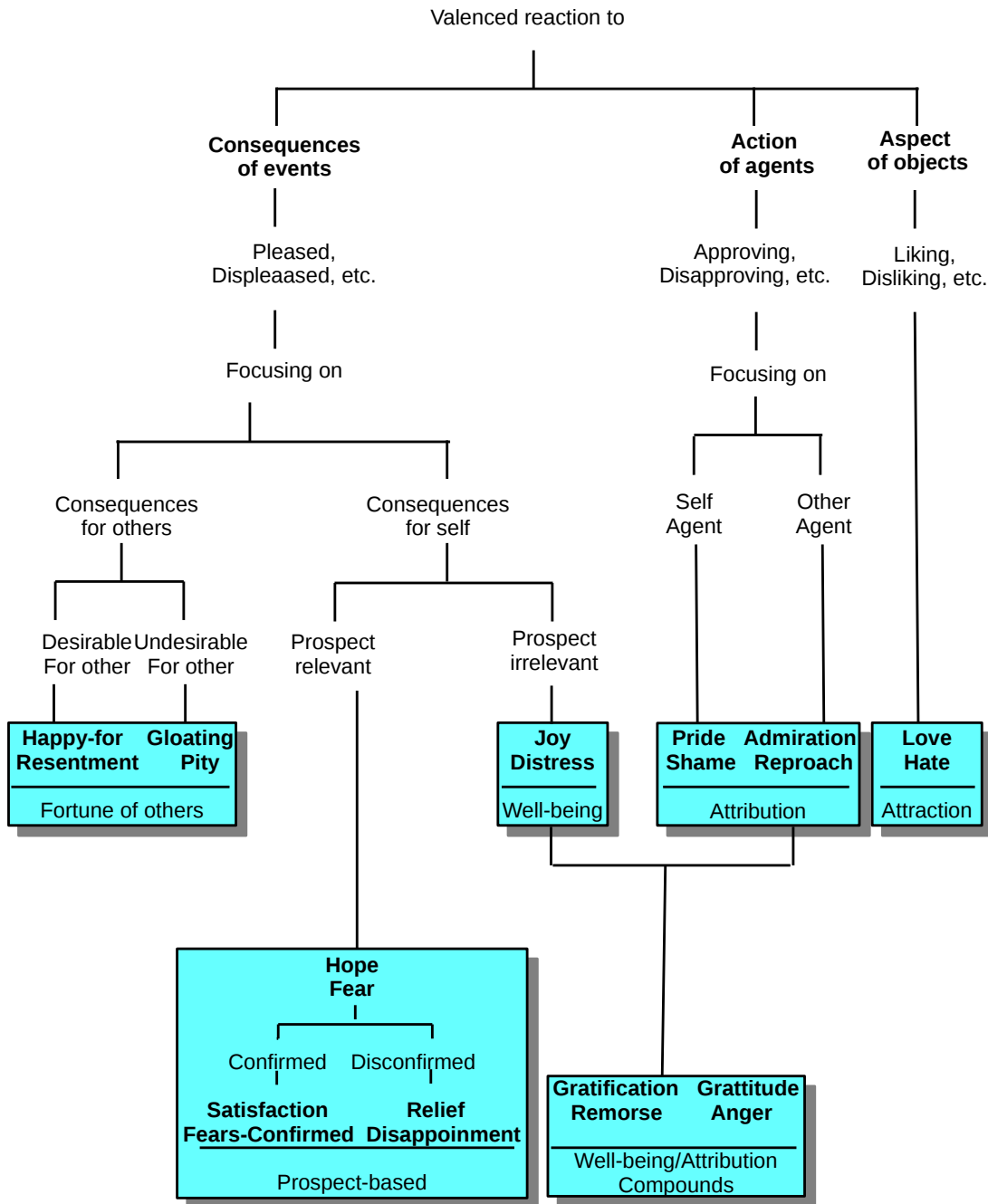


FIGURE 2.5: The OCC Model



## 2.2 Adaptation and Memory

Several works have shown the relationship between memory and emotions. Events associated with intense emotions are recalled with more detail than less emotional events (Heuer and Reisberg, 1992). It has been shown that specific emotions differ in their effects on memory. Happiness could lead to a general facilitation of the encoding of incoming information (Roseman, 1991). By contrast, anger is associated with attention to goals and better recall of agents who obstructed goals (Levine, 1996).

In order to equip our framework with a memory system, we inspected different types of memory recognized in the literature, which are presented in this section (shown in Fig. 2.6).

According to (Atkinson and Shiffrin, 1968), memory can be categorized in three types: Sensory Memory, Short-Term Memory, and Long-Term Memory. The Sensory Memory is the shortest-term memory. This is where are saved the impressions of sensory information (generally no longer than a second), when the stimulus is finished. The Short-Term Memory (also known as working memory) is able to store a small amount of information (7 + 2 items) for a short period of time (no longer than a minute). The Long-Term Memory

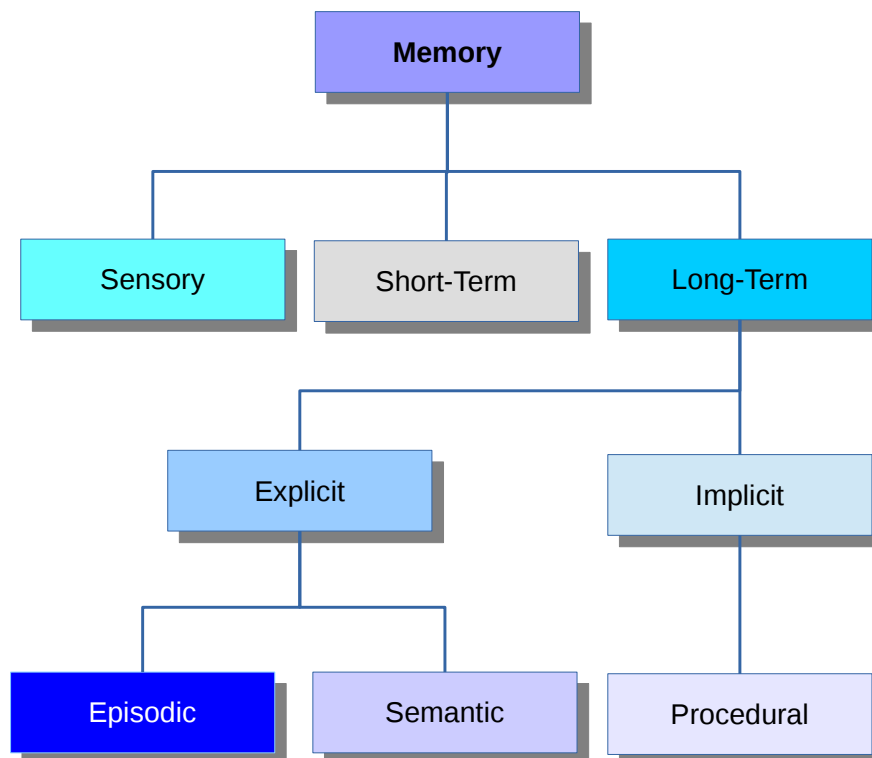


FIGURE 2.6: Memory types, based on the Atkison's Model

is all the information we can store for long periods of times (from minutes to years), and its capacity seems to be unlimited.

The Long-Term memory can be divided in Explicit (declarative) and Implicit (non declarative) parts. Declarative memory refers to all the events that can be consciously recalled, while the non declarative, is the information that is recalled unconsciously, here is located the procedural memory.

Explicit memory, is divided in two categories: Episodic Memory and Semantic Memory. The former is the ability to remember events from personal experiences, while the latter is the ability to remember concepts about the world.

### **Episodic Memory**

As we are more interested in social interactions, remembering events from personal experiences is of high importance for our work and this is strongly related to the Episodic Memory.

Tulving (Tulving, 2002) describes the Episodic Memory as a neurocognitive system, different from other memory systems, that enables human beings to remember past experiences. It shares features with the Semantic Memory but also possesses others features that the semantic memory does not have. An hypothesis is that this type of memory was built over other earlier systems, including the Semantic Memory.

According to Tulving (Tulving et al., 1972), some of the features that Episodic Memory shares with Semantic Memory are:

- Selectively receive information from perceptual systems.
- Retain various aspects of this information.
- Transmit specific retained information to other systems, including the one in charge of translating it into behavior.

And the features that are unique of the Episodic Memory are:

- Stores information about temporally dated events or episodes.
- Autobiographical references.
- The act of retrieving information also serves as input into the Episodic Memory, changing the contents on it.
- It is more susceptible to transformation and loss of information than the Semantic Memory.

From our point of view, these characteristics make the Episodic Memory the most suitable type of memory for companion robots. While interacting with robots in our daily life, we expect that they remember our preferences, but also that they adapt to our habits or any changes. For this reason, the robots should not only remember past events and the situations in which they happened, but also they should be capable of forgetting events that are no longer useful.

Other works including the use of episodic memory in robotic systems are (Dodd and Gutierrez, 2005), (Leconte, Ferland, and Michaud, 2014), (Kasap and Magnenat-Thalmann, 2010), (Nuxoll and Laird, 2004).

## 2.3 Behavior Theories

As social entities, we tend to treat computers and other media as if they were also social entities, as stated by Reeves and Nass in the Media Equation (Reeves and Nass, 1997). On certain occasions, we talk to computers even if they do not understand us. This happens because of our need to communicate in a natural way. This would be accentuated by robots who are physically embodied (have a body) and can talk to us. Then, if we want to achieve a natural interaction between humans and robots, we should need to base our work on the study of human behavior.

Because the aim of this work is to develop a framework capable of achieving a long-term Human-Robot interaction, the robot needs to adapt to its users. Human nature presents differences between one individual to another. Each person has different preferences, and so a robot behavior that can be seen as a good behavior for one person, can be perceived as inappropriate behavior for another person.

Individuals differ in many ways. Some of these differences are systematic and can be attributed to deeper differences, as the level of sociability and communication, or the level of anxiety that has a greater impact on solo behavior (Gill, Harrison, and Oberlander, 2004).

The problem of understanding human behavior has been studied for many years in the field of psychology. One of the notable first attempts to explain human behavior is by Freud, in his psychoanalysis theory and his studies on the unconscious (Freud, 1915). Freud compares the mind to an iceberg, where at the surface is the conscious mind, and below of that is found the pre-conscious, which is made of the thoughts that can be retrieved by memory, and finally, the biggest region is the unconscious mind, where are found

all our internal desires and primitive wishes, which govern our basic behavior.

Another theory of human behavior, called behaviorism, was developed by John Watson in his article "Psychology as behaviorist views it" (Watson, 1913). This theory, rejects the idea of the consciousness and focus on observable behavior, which can be measurable in an objective way.

Behaviorism was criticized by other researchers, who stated that using experiments with humans creates an artificial environment and low ecological validity. This approach is called Humanistic psychology, which states that humans can make their own decisions and do not follow a deterministic approach (Rogers, 1963).

Gordon Allport was one of the first psychologists who developed a Personality Trait Theory (Allport, 1937). This approach states that a person can be described in terms of traits. A trait can be seen as a behavior pattern that keeps constant through space and time. The combination of different traits and the different degrees of these, is what gives to an individual an specific personality. This theory is described in more details in section 2.3.1.

Other well-known theory of human behavior is the Cognitivism theory, also called Social Cognitive Theory, and was developed by Albert Bandura (Bandura, 1989). This theory focuses on the mental process of learning and the dynamic interplay between person, behavior, and environment. A contemporary Social Cognitive Theory is called Regulatory Focus Theory, which states that we have two internal mechanism of orientations, which affect our motivation and performance in having gains or avoiding losses. This theory is described in section 2.3.2. This theory is very important for our work, because it allows to increase the performance of the persons interacting with the robot, if the robot adopts the correct strategy based on the regulatory focus theory. For instance, a robot could be more motivating for a person who should exercise, and the person could have a better performance on the exercises.

### 2.3.1 Personality Trait Theories

We decided to focus on Personality-Trait theories because it gives a categorization of different kinds of personalities, and at the same time provides a differentiation between individuals. Also, this has been widely studied before in the field of Human-Computer Interaction (HCI), in order to embody virtual agents with personality (e.g., André et al., 2000a, Allbeck and Badler,

2002, Egges, Kshirsagar, and Magnenat-Thalmann, 2004). In social robotics, this has been also a topic of interest to provide robots with a personality that best fit with their users (Woods et al., 2005), (Tapus, Țăpuș, and Mataric, 2008), (Hendriks et al., 2011).

The personality trait theory has evolved over the years. Some of the most recognized theories in this domain are described next.

One of the first models of personality traits is the Gordon Allport's Trait Theory (Allport, 1937). This theory classifies the traits in three classes: Cardinal traits, Central traits, and Secondary traits. According with this theory, Cardinal traits are the traits that are developed by a person (i.e., kindness, greedy, honesty). Central traits are seen as common to all people and we have different degrees of them (i.e., friendliness, generosity, anxiety). Secondary traits are considered to be related with attitudes or preferences and only appear under certain situations. The total number of traits was found to be over 4000.

Eysenck proposed a model of only 3 personality traits (Eysenck, 1953): Introversion/Extroversion, Neuroticism/Emotional stability, and Psychoticism. This model was criticized for using a small sample and only self reporting as source.

Cattell reduced the number of traits from 4000 to 16 using factor analysis using different sources. He also developed a questionnaire to measure these 16 traits, called the Sixteen Personality Factor Questionnaire (16PF, Cattell, 1957).

A model emerged from these previous ones, called The Five Factor Theory of Personality, also called the Big Five personality trait (Norman, 1963). This model has 5 traits: Extroversion, Neuroticism, Agreeableness, Conscientiousness, and Openness. I will describe this model in more detail in the following section.

### **Big Five Personality Trait**

The first researcher who argued the existence of 5 traits of personality was Fiske (Fiske, 1949). Hereafter, a number of researchers have converged to the existence of 5 orthogonal factors (Norman, 1963, Goldberg, 1993, Digman, 1996). Even when there is no general consensus on a definitive theory of personality, this theory is the more accepted in the contemporary literature.

Researchers, who defend this theory, state that any reasonable large sample of English trait adjectives will elicit a variant of the Big Five factor structure, and then, all such terms can be represented within this model. It is

important to note that each trait can be seen as a dimension, each dimension has two facets, and each facet represent a group of adjectives. An example of the uniqueness of a personality, conformed by the five traits of this model, can be seen in Fig. 2.7.

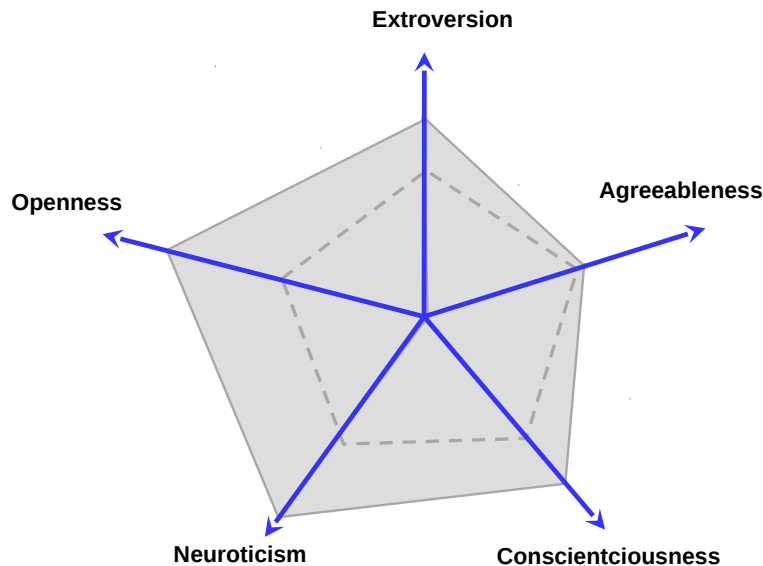


FIGURE 2.7: Big Five Personality Trait

This model is also sometimes called OCEAN by the initials of the traits. Next, some of the adjectives grouped by each trait are enumerated.

- Openness (Intellect):
  - High Openness: Intellectuality, depth, insight, intelligence, creativity, curiosity, sophistication.
  - Low Openness: Shallowness, unimagitiveness, imperceptiveness, stupidity.
- Conscientiousness:
  - High Conscientiousness: Organization, efficiency, dependability, precision, persistence, caution, punctuality, decisiveness.
  - Low Conscientiousness: Disorganization, negligence, inconsistency, forgetfulness, indecisiveness.
- Extroversion (Surgency):
  - High Extroversion (Extroversion): Playfulness, expressiveness, spontaneity, talkativeness, animation, courage, optimism.

- Low Extroversion (Introversion): Silence, reserve, shyness, inhibition, passivity, lethargy, pessimism.
- Agreeableness:
  - High Agreeableness: Cooperation, amiability, empathy, generosity, courtesy, flexibility, modesty.
  - Low Agreeableness: Belligerence, bossiness, cruelty, pomposity, irritability, prejudice, volatility.
- Neuroticism (Emotional Stability):
  - High Neuroticism: Insecurity, fear, instability, emotionality, envy, gullibility, intrusiveness.
  - Low Neuroticism: Placidity, independence.

A self-reported questionnaire, to measure the five personality traits of this model, was proposed by John and Srivastava, which consisted of 44 items in a 5-points Likert scale (John and Srivastava, 1999). Such questionnaire has been used (or adaptations of this) to perform numerous experiments on personality traits in social sciences and also in social robotics.

### 2.3.2 Regulatory Focus Theory

In the previous section, the personality traits theories were presented, which explain the differences and similarities between different individuals. Nevertheless, companion robots face the problem of motivating their users to do certain tasks on their schedule, such as taking medication, doing physical exercise, calling a member of their family, etc. Personality traits theories do not explain how to increase the inner motivation of the different personality types. For this reason, we investigated in the social psychology literature theories and models that could help us to deal with this.

We found the Regulatory Focus theory, proposed by Higgins (Higgins, 1998) to be very useful for increasing self motivation. This theory posits that people have one of two different inclinations for decision making, either promotion focus or prevention focus, where promotion focus is related with risk situations, and prevention focus is related with security. The inclination which is more emphasized in a person is called Chronic Regulatory Focus.

Chronic Promotion Focus people are more inspired by positive models, which emphasize strategies for achieving success. Chronic Prevention Focus

people are more inspired by negative models, which highlight strategies for avoiding failure. In this way, Promotion people focuses on obtaining more gains, and Prevention people focuses on not having losses.

The same theory shows that these states can be induced, naming these states as Induced Promotion Focus and Induced Prevention Focus.

Furthermore, there is another theory proposed by the same author, called Regulatory Fit theory (Higgins, 2000), which states that a match between an induced state and a chronic state leads to a greater motivation. And, a mismatch of the induced regulatory state with the chronic state can be counter-productive, resulting in a lower performance of a person in a task, and also an increase of that individual's stress level.

Accordingly with this theory, an increase of persuasiveness can be achieved by non-verbal cues such as body gestures and the speed of the speech. Making movements, leaning forward, and speaking more quickly, is more persuasive for people with Chronic Promotion State. Instead, making precision gestures and speaking more slowly, is more persuasive for people with Chronic Prevention State (Cesario and Higgins, 2008).



## 2.4 Conclusion

In this chapter, the psychological theories used in this research work were introduced.

Starting with the emotions theories, two big categories of these: Cognitive and Non-Cognitive Theories were presented. A small review of the main Cognitive Theories was discussed, together with the chosen emotion model for this work, the OCC Model.

Furthermore, a brief description of the memory types was presented. The Episodic Memory is the memory type that we considered to be the more pertinent for this work.

We continued with a brief review of the main behavioral theories, from where the personality theories evolved.

Finally, as the personality trait theory does not cover all the aspects desired in our research work, we chose a social cognitive theory, called the Regulatory Focus theory, which was also described in this chapter, and is of vital importance for increasing inner motivation on the users of personal robots.

One of the main challenges faced in this work, was the integration of all of these different theories.

In the next chapter, we present an experimental study showing a social issue present in a Human-Robot interaction, we implemented an emotional system and an episodic-like memory system in a Nao robot which interacted with the participants in a game-like scenario. In the following chapters the integration of all these aspects and how the conditions in which these theories can be applied in the context of Human-Robot Interaction are depicted.

## Chapter 3

# Integrating a Framework for Human-Robot Interaction

In this chapter, we present a robot interacting with a group of users in a game-like scenario, with the purpose of analyzing the users performance on the game in order to verify if a social issue called "Social Facilitation" (Zajonc et al., 1965) appears in Human-Robot Interaction as it appears in Human-Human Interaction. The Social Facilitation theory is described in section 3.1.1.

We introduce a high-level framework, which starts as an integration of an emotional model and an episodic memory. We started with an emotion based approach in order to give the robot a more believable behavior, capable of engaging the user in a more natural interaction.

The emotional model is a partial implementation of the Ortony Clore Collins Model (OCC Model) (Ortony, Clore, and Collins, 1990), implementing 6 emotions: love, hate, pride, shame, admiration, and reproach. These emotions falls in two categories of the model: *Aspect of Objects* and *Actions of Agents*.

The category of Actions of Agents is of particular importance for us because it relies on the performance of the actions of the agents, which in this case are the users interacting with the robot.

The OCC Model has been widely implemented in Human-Machine Interaction for virtual animated characters (André et al., 2000b) and robotics. The authors in (Kröse et al., 2003) present the development of a robot equipped with the OCC model for their emotion engine, but not in an interaction scenario, as is the case of this chapter.

Furthermore, in our work, we propose using an episodic memory (EM) using Adaptive Resonance Theory (ART) neural networks (EM-ART) (Carpenter and Grossberg, 1987), presented in (Wang et al., 2012) (Leconte, Ferland, and Michaud, 2014). The EM-ART records sequences of events as episodes.

This work presents a first step in the integration of the emotion system with the memory system, using EM-ART as long-term memory to provide useful information to the emotion system based on the OCC Model, and the output of this is used to modulate the intensity of different expressive behaviors.

## 3.1 Social Issues of Human-Robot Interaction

Companion robots will be more and more part of our daily lives in the coming years, and having long-term interactions with them can have both positive and negative effects on their users.

With robots being more and more around people, situations where social interactions have an effect (positive or negative) can appear more frequently. For this reason the robots need to be capable of adapting to the user so as to improve the interaction and the user's task performance.

This chapter presents an experiment focused on social facilitation, which is the evaluation of performance in the presence of others, as described in the social psychology literature. Our scenario is a memory game played with cards against a Nao robot. The robot has a framework combining an emotional system based on the OCC Model, and an episodic memory mechanism.

### 3.1.1 Social Facilitation

The aspect discussed in the work presented in this chapter is called Social Facilitation, which is a widely studied (Michaels et al., 1982) (Uziel, 2007) psychology paradigm introduced by (Zajonc et al., 1965), that states that individuals get a better performance on easy tasks if they are in the presence of others than doing the same task alone, but their performance is worse in complex tasks.

Very little work in social robotics (Wechsung et al., 2014) (Riether et al., 2012) or virtual characters (Park and Catrambone, 2007) has focused on Social Facilitation. The authors in Riether et al., 2012 presented a study that compared the task performance of 106 participants on easy and complex cognitive and motor tasks across three presence groups (alone, human presence, and robot presence). They found evidence that confirms the theory of Social Facilitation, but they focused on the mere presence of the robot.

This chapter presents an experiment where the social facilitation effect in Human-Robot Interaction is investigated. The scenario involves a memory card game in which the robot is the opponent of the human player, and it can take two roles: it can encourage or judge the human-user, depending on the game mode.

## 3.2 Choosing an Emotion Model for the Robot

In order to provide the robot with a mechanism capable of generating a natural behavior, we included in our framework an emotional system. The literature indicates the existence of mainly two broad categories of emotion models (cognitive and non-cognitive), which were reviewed in Chapter 2. A non-cognitive model has the advantage of providing a fast response to the robot, because it is more reactive. Nevertheless, we opted for a cognitive model because we wanted to have the capability of adapting the behavior of the robot during the interactions with its users, and this capability needs a memory and mechanism of reasoning about past events.

Among the cognitive models of emotion, there are many existing models, and some of them have been implemented on robotic systems, e.g., (Gadanh and Hallam, 2001), (Fellous, 2004), (Dodd and Gutierrez, 2005). We decided to use the OCC Model (Ortony, Clore, and Collins, 1990) because it has many desirable characteristics for us, such as a wide range of emotions, three categories based on objects, agents, and events, where the category of events include variables about past events to generate the emotions. Also, it has partially been implemented before on virtual animated characters (André et al., 2000b) and robotics (Kröse et al., 2003).

The OCC Model Ortony, Clore, and Collins, 1990 is based on 4 global variables and 12 local variables, each variable depending on both physical and psychological factors. The model has 22 emotions that are divided in three categories: *Aspect of Objects*, *Action of Agents*, and *Consequences of Events*. In this work, we focused on the category of Action of Agents for its relation with the social facilitation effect.

The synthesis of the emotions belonging to this category is described as follows:

### 3.2.1 Synthesis of Emotions

Let  $A(p, o, t)$  be the approving of action  $o$  that person  $p$  assigns at time  $t$ . This function returns a positive value if the performance of the action is above the standards for that action, and returns a negative value if the action does not meet the standards. The standard is a given value to determine if the performance is low or high. Let  $I_g(p, o, t)$  represent a combination of the global intensity variables. Let  $P_a(p, o, t)$  be the potential for generating a state of admiration. If the action is performed by others, the rules for admiration and reproach are presented in Algorithm 1.

---

#### Algorithm 1 Synthesis of Admiration and Reproach

---

```

set  $P_a(p, o, t) = f_p(A(p, o, t), I_g(p, o, t))$ 
if  $A(p, o, t) > 0$  then
  Given a threshold value  $T_a$ 
  if  $P_a(p, o, t) > T_a(p, t)$  then set  $I_a(p, o, t) = P_a(p, o, t) - T_a(p, t)$ 
  else set  $I_a(p, o, t) = 0$ 
  end if
else
  Given a threshold value  $T_r$ 
  if  $P_a(p, o, t) > T_r(p, t)$  then set  $I_r(p, o, t) = P_a(p, o, t) - T_r(p, t)$ 
  else set  $I_r(p, o, t) = 0$ 
  end if
end if

```

---

The approving function  $f_p$  is denoted by:

$$f_p = (Praise * SoR * CogUnit) + (Prox * a) + (Ar * b) \quad (3.1)$$

where *Praise* is the praiseworthiness, *SoR* is the sense of reality, *CogUnit* is the cognitive unit, meaning the grade of similarity between the preferences of the robot and the person, *Prox* is the proximity, *Ar* is the arousal and  $a$  and  $b$  are factors of increment set empirically to 0.1 and 0.3, respectively. The emotions of pride and shame were synthesized the same way, but based on the performance of the robot. The functions describing the arousal and the mood are presented in Algorithm 2. The threshold functions were denoted by a sigma function (3.2), and having as input the value of the mood. Also the arousal was processed with a s-shaped sigmoid function to limit its value.

Praiseworthiness (*Praise*) is of great importance in our case because it is related to the user performance on the task, as the emotions generated are based on the Actions of Agents, then the emotions are strongly linked with the value of this variable.

**Algorithm 2** Arousal and Mood

---

```

arousal = arousal +  $\sum_{i=1}^n$  intensity_emotion - (ti - ti-1) * 0.05
if arousal < 0 then arousal = 0
end if
if admiration or pride or love then
    mood = mood + intensity_emotion - (ti - ti-1) * 0.01
else [reproach or shame or hate]
    mood = mood - intensity_emotion - (ti - ti-1) * 0.01
end if

```

---

The value of *Praise* is defined by  $Praise = performance + (expDev)$ , where *expDev* is the expected deviation given by  $expDev = performance - lastPerformance$ . Then the *Praise* was processed with a sigma function denoted by:

$$y = (g / (1 + e^{-(x-x_0)/s})) + y_0 \quad (3.2)$$

where *s* is the change step of the sigmoid, *g* is the maximum value, *x*<sub>0</sub> is the half of the sigmoid, *y*<sub>0</sub> is used to give a positive or negative output and *x* is the input.

The parameters of the OCC Model were set up as: *Appealing* = 0.5, *Familiarity* = 0.1, *Praiseworthiness* = Player's performance, *Strength of Cognitive Unit*=1 for the robot's actions and 0.5 for the person's actions.

### 3.3 Giving an Episodic-Like Memory to the Robot

In this section, we provide a mechanism capable of adapting the behavior of the robot to previous interactions with the users. For this reason, we included a memory system, which also could be linked with our emotion system. It needed to be part of category of long memory, but at the same time could change over time. A short explanation of the memory types is presented earlier in 2. We opted for the Episodic Memory as it is the ability to remember personal experiences events (Atkinson and Shiffrin, 1968).

Our framework uses the EM-ART implementation presented in (Ferland, Cruz-Maya, and Tapus, 2015). The EM-ART model (Wang et al., 2012), shown in Fig. 3.1, is made of three layers: Input, Events, and Episodes. The Input Layer is used to represent the external context information. It is categorized in channels in which each node represents the presence of a known element with an associated activation level. The nodes found in the Events Layer represents elements in the Input Layer that were activated simultaneously.

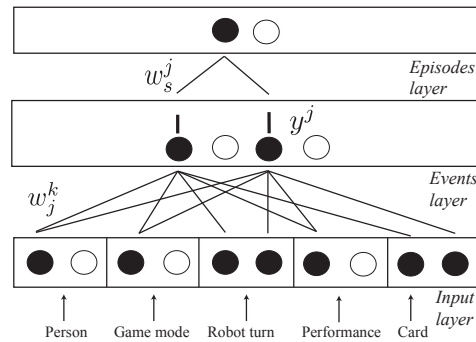


FIGURE 3.1: EM-ART Model with a recalled episode built out of 2 events.  $y^j$  represents the activation level of event  $j$ .

Synchronization of input elements is done by a short term memory buffer. As time progresses, the activation level of nodes in the Event layer decreases. Therefore, the sequence of events is represented by the pattern formed by those levels: the highest activation level is associated the most recent event to occur, and the lowest to the oldest. The Episodes Layer is made of nodes that categorize the patterns of the activation level of nodes in the Events Layer, thus defining episodes as temporal sequences of events. New episodes are created only when learning is triggered. In this work, learning is triggered at the end of each game to record its final sequence of events.

In Fig. 3.1 we depict an example of the Episodic-Like Memory used on this work, the input channels are explained in the next section.

### 3.4 Testing the Framework in a Game-Like Scenario

In order to test and validate our framework, we designed the "Find the Pair" board game. The "Find the Pair" board game is played with a set of cards containing pairs of matching images. The cards are put face down on a grid with letters marking columns from A to D and numbers marking rows 1 to 5. At each turn the player has to uncover two cards. If they are matching, the cards are removed and the player can uncover a new pair of cards, and so on. Players switch turns when a non-matching pair is uncovered. The game ends when all matching pairs have been discovered. The player with the most pairs wins.

The robot cannot manipulate the cards by itself. Instead, it says the letter and number of the desired card position, and then the user has to uncover it, enabling the robot to recognize the image of the card.

At each turn the players' performance is calculated based on the number of times uncovering a card in the same spot on multiple turns. At the end of the game the user's task performance is calculated based on the number of pairs.

The information about the players is stored in the EM-ART with 5 channels: Person, Game Difficulty, Robot turn, Performance, and Card. Where, Person is the name of the participant playing the game, Game Difficulty can take the values of "easy" or "difficult", Robot turn can take the values of "0" or "1" depending if it is the turn of the robot or not, Performance is the number of unveiled cards before matching the correct card, and Card is the number of the unveiled pair.

An event in the episodic memory corresponds to a turn in the game and an episode corresponds to a complete game.

The experimental conditions were defined by two factors, game difficulty level and presence of the robot. The game was tested with two levels of difficulty depending on the numbers of cards: 10 for the easy mode, and 20 for the difficult mode. Each participant played the game 3 times alone in both game modes before playing versus the robot, and 1 time versus the robot in each game mode.

### 3.4.1 Hypothesis

The hypothesis of this work are inspired by the Social Facilitation effect and are formulated as follows:

Hypothesis A: The user's performance in an easy task while being encouraged by a robot, will be better than while performing the same task alone.

Hypothesis B: The user's performance in a difficult task while being judged by a robot, will be worst than while performing the same task alone.

### 3.4.2 Robot Behaviors

The robot has eight behaviors: Greeting people, pointing to the cards, and expressing pride, shame, admiration, reproach, encouraging, and judging. Except for encouraging and judging, each behavior produces both speech and movement. For pride, the robot rise its arms at the height of its waist, for shame, the robot rise its right arm and cover its face with it, for admiration, the robot "claps" with its arms, and for reproach the robot moves its head from left to right and vice-versa two times. At each turn and at the end of the game, the robot can perform a body motion behavior or speak according to



the intensity of the emotions present in its internal state. Fig. 3.2 shows the emotional expressions of admiration and pride corresponding to the actions of agents of the OCC Model.

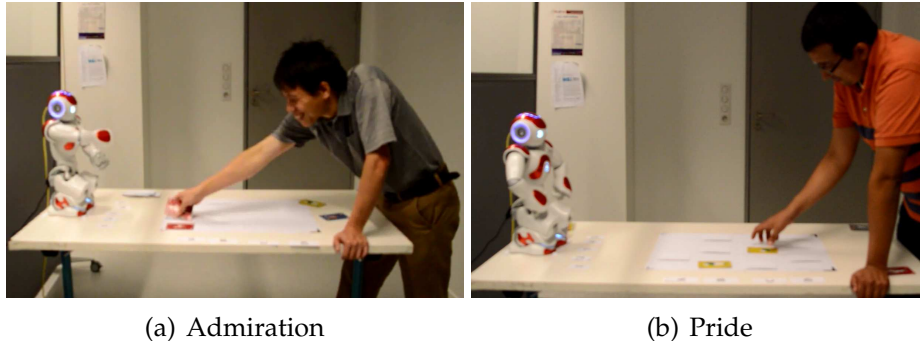


FIGURE 3.2: Robot Emotional Expressions

### 3.4.3 Methodology

The high level framework proposed is composed of face and card recognition modules, an episodic memory, a cognitive emotional system, a task specific module to play the "Find the pair" game, a database of the preferences of the robot, and an expression generator module.

The face recognition module generates a search in the episodic memory specified by the name of the person and the game level difficulty, which gives the information of the last played game, and it is sent to the speech generation module. Based on the performance on the task (e.g. "number of pairs obtained") and the attitude of the robot towards the person and the game, the emotional system generates responses that are communicated to the expression generator module.

Face Detection is done by using the Viola-Jones (Viola and Jones, 2004) method and Face Recognition with Local Binary Patterns (Ahonen, Hadid, and Pietikäinen, 2004), using the implementations provided by the OpenCV library. Card Recognition is based on FindObject2D<sup>1</sup>, an open source project that uses a bag-of-words approach with different types of 2D image features. Here, FindObject2D is configured to use the OpenCV implementation of FAST (Rosten, Porter, and Drummond, 2010) features on images incoming from the robot's camera.

The game board used was a white paper of A3 size, with 4cm wide square corners colored in black and set on a white table. For detection of the game

<sup>1</sup><http://introlab.github.io/find-object/>

board, the image was binarized with the Otsu method, and the Harris corner detection method was applied. Then, the region was transformed to correct perspective distortion and facilitate recognition of the cards. Game board detection and perspective correction was also implemented with OpenCV.

The experiment was done with a NAO robot from Aldebaran Robotics. The experiment was tested with 10 participants: 8 male and 2 female with ages in range from 22 to 34 years old and all with technical background. 4 of them had no prior interaction with a robot.

The measure of the performance for the Social Facilitation experiment was given by  $perform = errors/pairs\_obtained$ , where  $pairs\_obtained$  is the number of pairs obtained at the end of the game. An error is counted when a card has been shown previously and the person did not remember its position. The results are presented in Table 3.1. Paired t-tests for dependent means and two-tailed hypothesis were applied.

#### 3.4.4 Results and Discussion

The results were not statistically significant ( $p > 0.10$ ). The difference between the Easy level played alone and the Easy level played with robot conditions gave a  $t = -1.8653$  and a  $p = 0.0950$ ). The difference between the Difficult level played alone and the Difficult level played with robot conditions was more prominent and nearly to be statistically significant ( $t = 2.2003$ ,  $p = 0.0553$ ). This suggests that the mean errors counted in Easy mode was higher for the "playing alone" group (0.1788 vs. 0.0990), and the opposite in Difficult mode (0.3159 vs. 0.4810).

The differences in means are small, but can be explained by the small number of participants in the experiments. However, the results are nearly statistically significant, and they show a tendency in concordance with both hypotheses considered in this work. As expected for the theory of Social Facilitation, the performance is affected by the presence and behavior of the robot, improving it when the task is easy and worsen it when the task is difficult.

The internal emotional states of the robot are presented in Fig. 3.3, where the performance of the robot and one participant in difficult mode can be seen. In Fig 3.3(a), when the performance of the participant turns negative (under the standard), the intensity of reproach increases. On the other hand, when the performance of the participant increases, the intensity of admiration increases too. In Fig. 3.3(b), the performance of the robot along with the

TABLE 3.1: Mean and variance of participants' performance in the 4 game modes

|      | Easy Alone | Difficult Alone | Easy with robot | Difficult with robot |
|------|------------|-----------------|-----------------|----------------------|
| mean | 0.1788     | 0.3159          | 0.0990          | 0.4810               |
| var  | 0.0019     | 0.0211          | 0.0254          | 0.0837               |

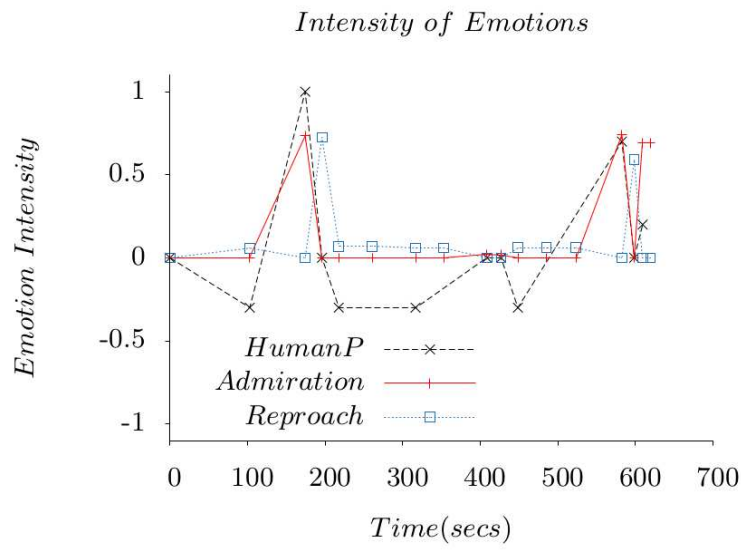
emotions of pride and shame can be observed. Even when pride was called during the game, at the end the raised emotion was shame because the standards were set to expect a high score of the robot. The mood and the arousal of the robot in this game are shown in Fig 3.3(c), where the mood can take negative values according to the synthesized emotions based on the performance of both players, decreasing with time and with negative emotions as shame and reproach, and increasing with positive emotions as pride and admiration. The arousal only has positive values, increasing with any kind of emotions, and decreasing at a higher rate than the mood.

The emotion system was analysed using a subjective measure of the participants with a post-experiment questionnaire <sup>2</sup>. Table 3.2 (Robot Behavior) shows the answers of the participants on a 7-point Likert scale, with 7 for strongly agree and 1 for strongly disagree (4 for neither agree or disagree). The answers of the participants show a clear recognition of the states of the robot in the different emotional states, which proves that the behaviors used were perceived as expected.

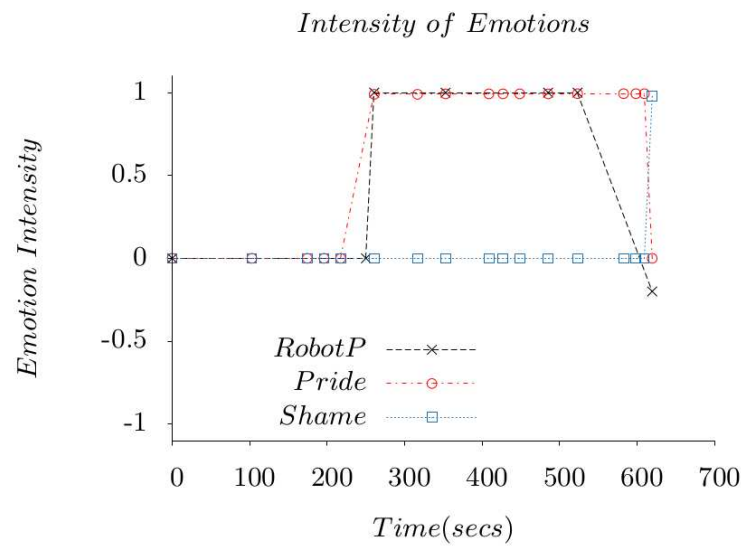
The negative mood was minimally present due to the fact that even when the person gets a pair in the game, the robot can show admiration and increase its positive mood. Also, the participants were asked two questions about their level of appreciation of the game in both modes (easy and difficult). The answers are shown in Table 3.2 (Game Mode), which are related to the variable *CogUnit* of the OCC Model. If the values of the attitude of the players towards the game had been used, the intensity of the generated emotions should had been higher, because they are more similar to the set value in the robot's preferences.

Finally, two open questions were asked to the participants to express their liking or disliking towards the robot, multiple answers were allowed. 5 participants liked the enthusiasm of the robot, 3 participants liked the correlation between the actions and the behaviors, 4 participants found the robot funny, and 1 participant found it clever. Six participants said that they disliked that

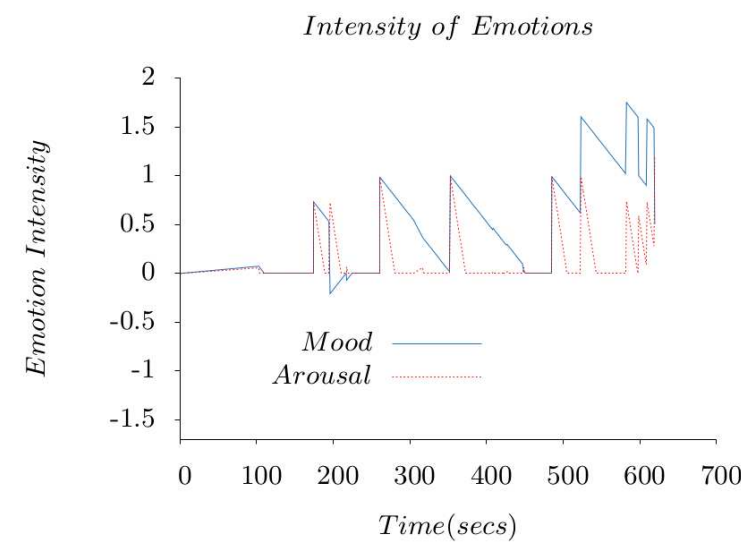
<sup>2</sup><http://goo.gl/forms/3TNI4KjvXu>



(a) Admiration - Reproach



(b) Pride - Shame



(c) Mood - Arousal

FIGURE 3.3: Human and Robot Performance and Robot's internal state of Mood and Arousal

TABLE 3.2: Participants' feedback

| <b>Robot Behavior</b>                       | <b>mode</b> | <b>mean</b> | <b>var</b> |
|---|-------------|-------------|------------|
| 1. Robot as good motivator in the easy game | 6           | 4.62        | 2.92       |
| 2. Robot disturbing in the difficult game   | 3           | 3.67        | 2.60       |
| 3. Positive mood when it was winning        | 6           | 5.83        | 0.69       |
| 4. Negative mood when it was losing         | 2,3,5       | 3.58        | 2.99       |
| 5. Admiration when in the easy game         | 4           | 3.75        | 3.47       |
| 6. Reproach in the difficult game           | 6           | 4.50        | 2.63       |
| 7. Pride when it was winning                | 7           | 6.17        | 0.69       |
| 8. Pride when it was losing                 | 3           | 2.92        | 1.90       |
| 9. Could be a good companion                | 6           | 5.50        | 1.72       |
| 10. Reproach when it was winning            | 4           | 3.67        | 3.33       |
| 11. Disturbing in the easy game             | 4           | 3.92        | 3.71       |
| 12. Motivating in the difficult game        | 4           | 3.67        | 2.60       |
| <b>Game mode</b>                            | <b>mode</b> | <b>mean</b> | <b>var</b> |
| 1. Easy                                     | 6           | 4.91        | 2.29       |
| 2. Difficult                                | 6           | 5.82        | 0.76       |

the robot was too egocentric. This can be explained due to the fact that we wanted that the person feel being evaluated in the difficult mode.

### 3.5 Contributions and Conclusion

The main contribution of this chapter is the use of a robot with an emotion system facing the social facilitation effect in an interaction scenario. Results showed a tendency to reinforce the social facilitation theory, which makes us believe that this should have to be considered for companion robots where the interaction in everyday life can provoke stressful situations for the humans.

We also presented the first state of our framework (an emotional system based on the OCC Mode and an episodic like memory system) in a Human-Robot Interaction context that involves a social facilitation effect.

These kind of robots have to adapt to their users through their interaction, and an emotional system can take place to manage the robot's behaviors.

For that reason, in the following chapters, we continue to explore different ways to adapt the behavior of the robot to different persons, and continue the implementation of the OCC Model, which is a very extensive model that include a large range of emotions, where memory plays an important role.

The EM-ART needs to be combined in a deeper way with the emotional system, because memory is the base of the section consequences of events of this model.

The work done on this chapter, was presented in the International Conference on Social Robotics (ICSR), Paris, 2015, (Cruz-Maya, Ferland, and Tapus, 2015).

In the next chapter, we introduce the use of a personality model to adapt the behavior of the robot to different users.



## Chapter 4

# Need of a User Pattern for a Personalized Interaction

Having robots helping us with our daily activities led to the need of endowing them with social capabilities in order to adapt their behavior to the environment and the various tasks. Nevertheless, how to achieve this adaptation remains a challenge.

An important feature for social intelligent robots is the use of long-term memory to keep information about past events to use in new events (Leconte, Ferland, and Michaud, 2015). In the previous chapter, we presented our framework, which included the use of an episodic-like memory system. Other important features for social robotics are the synthesis and recognition of emotions in order to be more appealing to humans and to be perceived as more useful and expressive (Kishi et al., 2013). For that reasons, we included in our framework an emotional system based on the OCC model.

The system should work with the primary users of the robot and learn through interaction with them. However, when the robot is exposed to more people other than their primary users, for example relatives or friends, the robot should behave in an appropriate manner and in most of the cases the robot does not have enough information about past interactions.

This situation can happen also with the primary users of the robot when unencountered situations between the robot and the user occur. For example, the robot learns how to motivate the users to perform their daily exercises by showing different emotions according to the performance of the users, but the situation could be totally different when the users feel sad or are in a different mood than expected. This is only an example that shows the need of an adaptive behavior when there is no information about past events.

A review of the literature (see Chapter 2) shows that personality plays an important role in behavior adaptation. Personality trait theories give a



categorization of different kinds of personalities (behavior patterns), and at the same time provide a differentiation between individuals.

Personality is an important factor in human social interaction, and has a long-term consistent effect on the generated human multimodal behavior. The authors in (Reisenzein and Weber, 2009) defined personality as the coherent and collective pattern of emotion, cognition, behavior, and goals over time and space. Therefore, it is important to consider the relationship between personality, goals, and performance in human-robot interaction.

In this chapter, we present our first study on the relation between a user's personality and robot reminders on a set of 9 different conditions. This is of high importance to us in order to obtain information about preferences and performance of people with different personalities. Robots are and will be more and more part of our everyday life, and they will sometimes have to interrupt us during our daily tasks. Thus, we need to find out the best approach to do it and investigate if the personality of the user is an important factor. To the best of our knowledge, there are no studies about personality and robot reminders.

## 4.1 Choosing a Personality Model

The first step in our research about personality was choosing a model of personality, we opted for the use of the most accepted personality trait model in the contemporary literature, which is the Big 5 personality trait (Norman, 1963) (Digman, 1996). The proponents of this model state that it can represent any reasonable large sample of English trait adjectives (Goldberg, 1993).

It is important to notice that we use the personality trait model to analyze the user's personality, and then we also use it as an input for the robot behavior. In this way, the robots can be endowed with various personality traits according to the different types of tasks to be performed (Joose et al., 2013) (Tapus, Țăpuș, and Matarić, 2008).

The Big 5 personality model is composed of 5 traits that can be seen as dimensions. In this study, we analyzed 2 of these dimensions. The first one is the extroversion, where the low level of the category can be seen as introversion and the high level as extroversion. The second trait is the conscientiousness, we refer to it as high conscientiousness and low conscientiousness to its high and low level, respectively.

## 4.2 Differences between Introverts and Extroverts

Works in social psychology have shown that people with different kinds of personality have different preferences when interacting. According to (Williams, 1971) extroverts allow closer interactions than introverts, but this can be influenced depending on the height of the persons (Caplan and Goldman, 1981). Likewise, smiling have proved to have an impact on the behavior of others (Stins et al., 2011). In social robotics, the effects of extroversion have been studied, for example, in (Andrist, Mutlu, and Tapus, 2015), the authors showed the use of gaze to increase motivation on the users interacting with the robot depending on the personality trait of extroversion.

A study done by (Syrdal et al., 2007) presents some differences on spatial preferences in HRI based on the personality of the users. It was found that participants scoring high on extroversion allowed the robot to come closer when the human was in control of the experiment than participants with a low extroversion score (introverts). Nevertheless, introverts were more comfortable with the robot coming closer when the robot was in control, while extroverts were less comfortable in this condition.

Other study about personality and preferences in the direction from which a robot approached the participants is presented in (Syrdal et al., 2006). They used the Big 5 personality model to assess personality, and concluded that higher extraversion scores are associated with slightly higher degrees of tolerance to robot behaviour that is less appropriate for the situation.

In previous work (Tapus, Țăpuș, and Matarić, 2008), was demonstrated a behavior adaptation system capable of adjusting its social interaction parameters (e.g., interaction distances/proxemics, speed, and vocal content) toward customized post-stroke rehabilitation therapy based on the user's personality traits and task performance.

## 4.3 Differences between People with High Conscientiousness and People with Low Conscientiousness

In an earlier study (Barrick and Mount, 1991), they showed that the most consistent personality predictor for task performance is conscientiousness.

Some adjectives that are usually used to describe people with High Conscientiousness are: organized, efficient, independent, precise, persistent, cautious, punctual, and decisive. While people with Low Conscientiousness are generally described as: disorganized, negligent, inconsistent, forgetful, and indecisive.

In the study of spatial preferences presented in (Syrdal et al., 2007), participants scoring low on conscientiousness allowed the robot to approach them more closely when the human was in control than they did on the condition where the robot was in control.

## 4.4 Methods

### 4.4.1 Case Study: Office-Like Scenario with a Robot Giving Reminders

One of the main purposes of companion robots is to use them to remind their users about the tasks they have to do. The interaction requires robots to adapt to the person with respect to their preferences and therefore to take into consideration the inter-individuals and intra-individuals differences.

The performance of the human when a robot reminds them to do a certain task is of great importance. For example, if a robot reminds its user to take some medication, it is important that the user really takes the medication. Findings in social psychology show that personality influences the way that humans interact. In this work, we conducted an experiment of task reminders in an office-like environment with a robot reminding tasks to a person while the person is doing other office-activities.

We present the effect on performance with respect to three interaction parameters (i.e., distance, height, and smile) in relation with two traits of personality of the user (i.e., conscientiousness and extroversion). The scenario is an office-like environment where the robot provides reminders of a schedule to the participant while the participant is busy with another task.

The scenario used to test and validate our hypotheses is an office-like environment, shown in Figure 4.1, where the user is asked to reply to as many e-mails as he/she can in a series of 10 e-mails. The total allotted time is 6 minutes. Two e-mails are labeled as urgent: one is a reminder of a meeting, and the other is a request for an activity report that should consist of 30 to 100 words. The others 8 e-mails are related to personal or work relations, where the user can reply with short answers. At the same time, a schedule



FIGURE 4.1: Office-like scenario with the Meka M-1 robot

to follow is given to the user, but the user is free to choose if he/she wants to follow the schedule or not. The schedule marks a break between minutes 2 to 4 after the beginning of the activity, and an important meeting between minutes 4 to 6. One minute before the specified time of the activities and at the exact time of these, the robot approaches the user to remind him/her of the activities.

#### 4.4.2 Hypotheses

Based on the above statements and the literature, we elaborated the following hypotheses:

- H1. High Conscientiousness people perform better in time when reminded by a robot than Low Conscientiousness people.
- H2. Close interaction, at the limit of interpersonal distance (Hall, 1966), will be preferred by extroverted people and far interaction (1.5 times the limit of interpersonal distance) will be preferred by the introverted people in the task reminder.
- H3. Participants will prefer to interact with a small robot rather than with a tall robot.
- H4. Participants will be influenced to finish a task earlier when the robot shows a smile on its face.

### 4.4.3 Robot Behavior

The robot used in this experiment is the robot Meka M-1, which is a wheeled humanoid robot that has been designed to work in human-centered environments. At the moment of the reminder, the robot goes in front of the participant and reminds him/her of the activity on the schedule. After that, it waits for the response of the participant.

In order to avoid speech recognition system limits (in the case of non-native English speakers), the user answers by showing a card that is recognized by the robot. There are 4 cards with meanings of: 1. "Thank you", 2. "Remind me later", 3. "I already did it", and 4. "Don't remind me again". If the user shows the cards 3 or 4, the robot will not remind that activity again.

The reminders of the robot were designed in consideration of the criteria for good reminders (Reason, 2002), and their verbal content is presented as follows:

- Taking a break: "Hello, remember to take a break from your computer".
- Going to a meeting: "I would like to remind you about the meeting with your boss in few minutes. It will take place in the Meeting room".

In order to avoid repetitions, two different phrases with similar meaning have been developed for each reminder.

### 4.4.4 Pre-experiment Questionnaire

We recruited 16 participants for this experiment (4 Female, 12 Male) from ENSTA ParisTech university campus. Participant ages ranged from 21 to 32, all with technical background.

Participants were asked to fill out the Big Five inventory prior to participation so as to determine their position on the extroversion-introversion spectrum (Goldberg, 1990). This questionnaire contains 44 items each with 5-point Likert scale that ask the participant to rate their agreement or disagreement with statements about their own personality and activities. The score of the test gives values between 1 to 5. People with a score  $\leq 3$  on a personality trait was considered in the low category of the examined personality trait. For our study, we looked only at the extroversion and conscientiousness traits.

For the conscientiousness trait, we selected 4 participants with low conscientiousness, 4 participants with high conscientiousness, in both groups there

TABLE 4.1: Robot factors varying for each condition

| Condition | Code | Height | Distance | Smile |
|-----------|------|--------|----------|-------|
| 1         | —    | NA     | NA       | NA    |
| 2         | TCN  | Tall   | Close    | Off   |
| 3         | TCE  | Tall   | Close    | On    |
| 4         | TFN  | Tall   | Far      | Off   |
| 5         | TFE  | Tall   | Far      | On    |
| 6         | SCN  | Small  | Close    | Off   |
| 7         | SCE  | Small  | Close    | On    |
| 8         | SFN  | Small  | Far      | Off   |
| 9         | SFE  | Small  | Far      | On    |

were 2 participants scoring low on extroversion and 2 participants scoring high on extroversion. For the extroversion group we selected 4 participants with low extroversion (introverted), and 4 participants with high extroversion (extroverted), all of them with a score bigger than 3 on conscientiousness.

#### 4.4.5 Conditions

The study followed a 2x9 within-participants study design, with participant personality traits (extroversion/introversion and high/low conscientiousness, traits separately examined) and robot behavior as factors. The participants were divided in 4 groups according to the two traits of personality: Conscientiousness and Extroversion. The comparison on personality was done between High Conscientiousness and Low Conscientiousness individuals, and between Extroverted and Introverted individuals, having eight individuals in each personality trait.

The first condition was realized without the robot, and thus no reminders were provided. The next eight robot conditions were done with the combination of the 3 parameters (independent variables) to test: height of the robot, distance between the user and the robot at the moment of the reminder, and the smiling of the robot. The conditions were applied in the same order to all the participants, but the risk of learning the task was minimized by using different e-mails to reply on each condition. The conditions are listed in Table 4.1, where the values of the different variables of the robot are shown.

The 3 parameters (height/proxemics/smile) defining robot's behavior are:

1. Distance. Close: 1.2 m, which is the limit of the interpersonal distance according to (Hall, 1966). Far: 1.8 m, (1.5 x minimum interpersonal

TABLE 4.2: Post-Experiment Questionnaire

|     |   |
|-----|---|
| Q12 | You felt pressured by the robot reminding you the tasks to do:<br>not at all/ a lot   |
| Q14 | The robot was: Strongly disagree / Strongly agree<br>Q14.a Social - Q14.b Attentive - Q14.c Stressful - Q14.d Helpful                                       |
| Q15 | The robot was expressive: Strongly disagree / Strongly agree  |
| Q18 | Did you think the robot was acting intelligently? not at all / a lot  |
| Q19 | What characteristics made the robot more efficient in the<br>reminding task:<br>Q19.a Speech - Q19.b Height - Q19.c Proxemics - Q19.d Facial<br>expressions |

distance)

2. Height. Small: 1 m. Approx. height of a person sitting. Tall: 1.8 m. Approx. height of a person standing up .
3. Smile. Smile off: Robot without facial expression. Smile on: The face of the robot shows a smile drawn by the Meka LED matrix.

#### 4.4.6 Post-experiment Questionnaire

A post-experiment 5-points Likert scale questionnaire (33 items) was conducted after each condition. This questionnaire was done with the purpose of analyzing the perception of the participants towards the robot and search for relations between the variables of the study and the perceived influence on the task. Other questions are related to the perceived usefulness of the robot in the reminder task, perceived personality of the robot, and stress caused by the robot. The questions of the most relevant results are shown in Table 4.2, the complete list of the questions can be seen online<sup>1</sup>.

## 4.5 Results and Discussion

The time participants took to finish the experiment was used to measure the efficiency of the robot's reminders.

<sup>1</sup><http://goo.gl/forms/7OrESYgUtUp7esbD2>

TABLE 4.3: Results of ANOVA tests on time performance of conditions 2-9.

| High Conscientiousness. |         | Low Conscientiousness |           |  |
|-------------------------|---------|-----------------------|-----------|--|
| Mean                    | std dev | Mean                  | std dev   |  |
| 4.1984                  | 0.8948  | 5.1340                | 0.8784    |  |
| Sum sq                  | Mean sq | Df                    | p         |  |
| 14.016                  | 14.0157 | 1                     | 8.051e-05 |  |
| Extroversion            |         | Introversion          |           |  |
| Mean                    | std dev | Mean                  | std dev   |  |
| 4.8600                  | 1.2781  | 3.9081                | 0.6879    |  |
| Sum sq                  | Mean sq | Df                    | p         |  |
| 4.353                   | 4.3529  | 1                     | 0.047     |  |

We did a series of ANOVA tests, preceded by a Shapiro test to verify the normality of the data. We analyzed the performance on time for Conscientiousness and Extroversion separately, comparing introverts with extroverts and high conscientiousness people with low conscientiousness people.

We did not find significant differences on time performance related to the different conditions and each personality trait.

We found significant differences between extroverts and introverts ( $p = 0.047$ ) showing a better time performance of the introverts, as well as between high conscientiousness and low conscientiousness people ( $p = 8.051e-05$ ) showing a better time performance of the high conscientiousness people. The results of an one-way ANOVA test for each comparison of extroversion and conscientiousness are presented in Table 4.3. The means for the performance in time of each group are shown in Fig. 4.2a and Fig. 4.2b.

A paired Student's T-Test was applied to each group to analyze the differences of the time on each condition, the groups of Extroverts and Low Conscientiousness people did not show any significant difference between the condition without the robot and the conditions with the robot. The results suggests that introverted participants took significantly less time to perform the task when reminded by the robot, the p-values and means of the time are presented in Table 4.4. We only show the results of introverted and high conscientiousness participants because only in these groups we detected significant differences, and it should not be understood as a comparison between them.

The post-experiment questionnaire was analyzed applying a factorial ANOVA



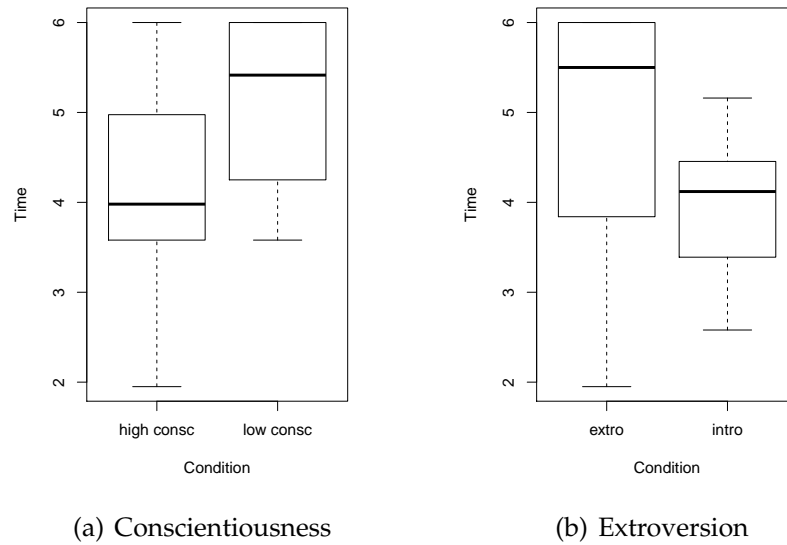


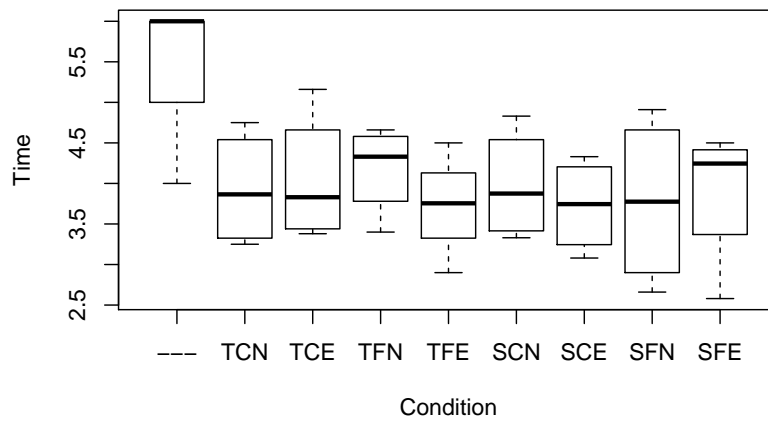
FIGURE 4.2: a) high conscientiousness people got better performance than low conscientiousness people. b) Introverted people got better performance than extroverted people.

TABLE 4.4: Mean and Standard deviation of time (min.) of the participants on the task, and p-value of the t-test between condition 1 and conditions 2-9.

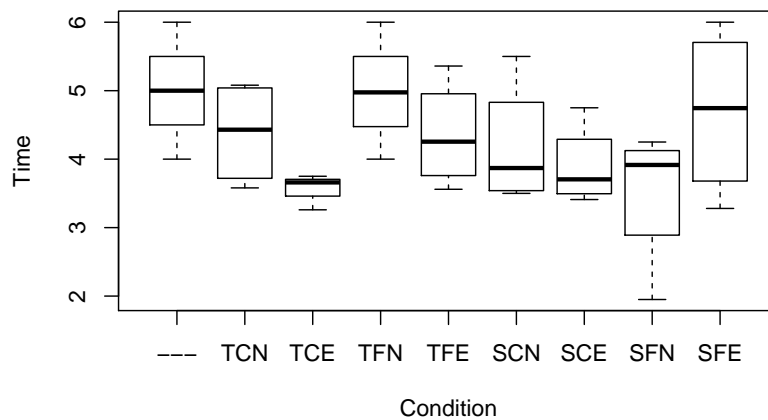
Introverted participants showed an improvement on time in all the conditions with the robot. High conscientiousness participants showed a significant improvement only in 2 conditions with the robot.

| Condition | Introversion           |               | High Conscientiousness |               |
|-----------|------------------------|---------------|------------------------|---------------|
|           | Mean (SD)              | p-value       | Mean (SD)              | p-value       |
| 1 —       | 5.5000 (1.0000)        | -             | 5.0000 (0.9847)        | -             |
| 2 TCN     | <b>3.9325 (0.7247)</b> | <b>0.0094</b> | 4.3800 (1.0346)        | 0.3090        |
| 3 TCE     | <b>4.0500 (0.8155)</b> | <b>0.0153</b> | <b>3.5825 (1.0328)</b> | <b>0.0250</b> |
| 4 TFN     | <b>4.1800 (0.5602)</b> | <b>0.0260</b> | 4.9875 (0.9373)        | 0.9830        |
| 5 TFE     | <b>3.7275 (0.6539)</b> | <b>0.0038</b> | 4.3575 (1.0329)        | 0.2920        |
| 6 SCN     | <b>3.9775 (0.6948)</b> | <b>0.0113</b> | 4.1850 (1.0811)        | 0.1840        |
| 7 SCE     | <b>3.7250 (0.5794)</b> | <b>0.0038</b> | 3.8925 (1.1360)        | 0.0750        |
| 8 SFN     | <b>3.7800 (1.0547)</b> | <b>0.0048</b> | <b>3.5075 (1.5394)</b> | <b>0.0190</b> |
| 9 SFE     | <b>3.8925 (0.8859)</b> | <b>0.0079</b> | 4.6925 (1.5394)        | 0.6110        |

test for each question for each personality trait, with the questions as dependent variables and personality of the participants, and distance, height, and smile of the robot as independent variables. The most relevant results of the ANOVA test are shown in Table 4.5. The means and standard deviations of



(a) Introversion



(b) High Conscientiousness

FIGURE 4.3: a) Introverts improved their performance in time in all the conditions with the robot compared with the condition without the robot. b) High conscientiousness people improved their performance in time only in 2 conditions with the robot.

the questions with the most relevant results are presented in Table 4.6.

TABLE 4.5: Post-Experiment Questionnaire's results. Most relevant results shows significant differences on height on both personality traits and smile in the conscientiousness group and distance in the extroversion group.

| (a) Conscientiousness |        |        |         |    |        |
|-----------------------|--------|--------|---------|----|--------|
| Q.                    | Var.   | Sum sq | Mean sq | Df | P      |
| Q14c                  | height | 11.391 | 11.390  | 1  | 0.0089 |
| Q15                   | smile  | 5.641  | 5.640   | 1  | 0.0206 |
| Q19d                  | smile  | 5.063  | 5.062   | 1  | 0.0236 |

| (b) Extroversion |        |        |         |    |        |
|------------------|--------|--------|---------|----|--------|
| Q.               | Vari.  | Sum sq | Mean sq | Df | P      |
| Q12              | height | 16.844 | 16.843  | 1  | 0.0002 |
| Q14c             | height | 9.766  | 9.765   | 1  | 0.0005 |
| Q18              | dist   | 4.516  | 4.515   | 1  | 0.0451 |

In the conscientiousness group, the height of the robot influenced the perception of dominance and stressful personality on it, increasing when the robot was tall. The robot was found to be more expressive when the robot showed the smile, and also this characteristic was rated to made the robot more efficient in the reminded task. In the extroversion group, the height of the robot when it was tall, was related with pressure and stress. The smile on the robot increased the perception of intelligence on it. Extroverted people found the robot more extroverted, attentive, helpful, and expressive than introverted people.

TABLE 4.6: a) People in the conscientiousness group perceived the robot more stressful(Q14c) in the tall condition, and more expressive(Q15, Q19d) in the smile condition. b) People in the extroversion group perceived the robot more aggressive (Q12) and stressful(Q14c) in the tall condition, and more intelligent(Q18) showing the smile in the close condition.

| (a) Conscientiousness |               |               | (b) Extroversion |               |               |
|-----------------------|---------------|---------------|------------------|---------------|---------------|
|                       | Small         | Tall          |                  | Small         | Tall          |
|                       | Mean (SD)     | Mean (SD)     |                  | Mean (SD)     | Mean (SD)     |
| Q14c                  | 2.000 (1.135) | 2.843 (1.167) | Q12              | 1.903 (0.830) | 2.806 (1.216) |
|                       | Smile On      | Smile Off     | Q14c             | 2.187 (0.859) | 2.968 (0.860) |
|                       | Mean (SD)     | Mean (SD)     |                  | Close         | Far           |
| Q15                   | 2.406 (1.160) | 1.812 (0.692) |                  | Mean (SD)     | Mean (SD)     |
| Q19d                  | 1.843 (1.167) | 1.281 (0.634) | Q18              | 3.187 (0.859) | 2.656 (1.065) |

## 4.6 Contributions and Conclusion

The main contribution of this chapter is the evidence that supports the literature about the personality traits of extroversion and conscientiousness, and that this can be applied to Human-Robot Interaction.

We found greater performance of high conscientiousness people over low conscientiousness people, and the results suggest that introverted people are more influenced to finish the task earlier than extroverted people.

The results suggest that the Hypothesis 1 (H1) is supported, because of the significant differences on the means of the time between high conscientiousness and low conscientiousness groups.

Results from the questionnaire give us information to evaluate hypotheses H2 and H3. Hypothesis H2 is only partially supported by the higher rating on intelligence by extroverts than introverts in the close conditions. Hypothesis H3 is supported by the relation between the small robot and the smaller ranking for pressure and stress in both personality traits. H4 should be rejected, as there is no evidence that supports it.

We conclude that robots could be helpful for reminding tasks for people with high conscientiousness and introversion while they are working in a daily activity, this is only taking in consideration the factors used in the experiments (i.e., distance, height, and smile). For people with extroversion and low conscientiousness other factors may be of greater help to motivate them to perform the task required.

In this chapter, we developed a robot behavior to remind tasks to the users in an office-like environment. The behavior was designed in consideration of the criteria for good reminders (Reason, 2002), and implemented in a Meka M-1 robot, which used object recognition to get the feedback of the users.

The work done on this chapter, was presented in the International Conference on Social Robotics (ICSR), Kansas City, U.S.A., 2016, (Cruz-Maya and Tapus, 2016a).

In the next chapters, we continue studying the effects of these and other conditions that help to adapt the behavior of the robot to different personalities, and also reaching the objective of minimizing the stress caused to the users.



## Chapter 5

# Effects of Stress and Personality in HRI using Multimedia Learning

In Chapter 4, we presented the study of personality in a social context between a robot and a human. In the current chapter, we focus on analyzing the possible connections between user's personality and the stress caused to the user by the social robot in a context of Multimedia Learning. Furthermore, we investigate the importance of the system's voice (synthesized vs. human), of the embodiment (robot vs. tablet), and of the user's gender and personality on learning nutrition and healthy eating tips.

Social robots have a great potential for helping people in their daily activities, especially in tasks that need one-on-one interaction, as it is the case of elderly people or children. Nevertheless, interacting with a robot can also provoke stress on the users (Sorostinean, Ferland, and Tapus, 2015). Here, we investigated the effects of stress and personality in Human-Robot Interaction in a context of multimedia learning using a robot as the embodiment of the presented multimedia.

As previously mentioned, personality plays an important role in social interaction but also in learning. It was shown in the literature that the user's personality is strongly linked with the performance on academic grades and learning. More precisely, the conscientiousness trait has been shown to have a significant relation with good academic grades, extroversion with lower grades, and neuroticism with good scores on tests (Rosander, Bäckström, and Stenberg, 2011). For these reasons, we take into consideration the user's personality type and we investigate the influence of the user personality traits for learning nutrition and healthy eating tips.

Moreover, evaluating the learning process of the users can be used as a guide to increase or decrease the difficulty of the learning session. However, increased cognitive workload and a low score on tests can be a source of stress (Ross, Niebling, and Heckert, 1999). We posit that monitoring the

user's stress is important. We would like to measure the stress in a non-invasive and contact free way, for which we can take advantage of the body's naturally emitted thermal radiation, using a thermal infrared camera. This thermal radiation is caused by our body processes part of the nervous system, such as the heart beating, breathing, perspiration, among others, which can be used to made inferences about our emotional state (Ioannou, Gallese, and Merla, 2014). A review of thermal infrared imaging in psycho-physiology is presented in (Ioannou, Gallese, and Merla, 2014) where a decrease of the temperature on the nose of the participants is linked with an increase of stress.

In a previous study done in our laboratory (Autonomous Systems and Robotics lab) (Sorostinean, Ferland, and Tapus, 2015), the stress caused by a robot was already presented and face temperature variation was measured with a thermal camera. The results show significant variation in temperature in the nose region of the participants when they are stressed. Therefore, in this work, by using a thermal camera, we also measure the temperature of the nose tip region of the participants to analyze the stress caused to the participants of the experiment.

In this chapter, we wanted to investigate if the robot's embodiment, and machine voice were more stressing for users than a tablet computer and human voice. We also analyzed the relation of user's personality and four conditions combining the voice and embodiment. We developed a multimedia presentation in HTML and javascript based on the guide for Multimedia Learning proposed by (Mayer, 2014a), which was presented on a Kompai robot and a tablet computer to different groups of users separately.

## 5.1 Robots Used for Teaching

Using robots as teachers or assistant teachers has been object of research in the last years. The authors in (You et al., 2006) used a robot as assistant teacher for children in an English learning classroom. Moreover, Tanaka et al. (Tanaka and Matsuzoe, 2012) used the Nao robot for teaching children new vocabulary.

Having a robot at home in charge of reminding elderly people and/or teaching children how to have a healthy diet could have a positive impact on their lives. It has been shown that a higher quality diet is related with a decreased risk of cancer and cardiovascular diseases (Reedy et al., 2014), diabetes (Hu, 2011), and obesity (Nicklas et al., 2001). In this context, we

are focusing on this task here, presenting our multimedia presentation, described in Section 5.3.1, with the purpose of studying personality preferences and its relation with user stress in a Multimedia Learning scenario.

## 5.2 Multimedia Learning

Electronic Health interventions for physical and dietary behavior have been done in numerous cases, using web applications for computers or mobile-phones. For example, the authors in (Brug et al., 1996) showed the impact of computer intervention on nutrition, pollak2010s presented the use of mobile-phones to promote healthy eating, and a review is presented in (Hingle et al., 2013) where the results show a potential of this technology but also the need for more rigorous evaluations.

Mayer states in his Multimedia Learning Theory (Mayer, 2002), that there are social cues like voice and embodiment that affect learning. In his work with virtual agents, human voice and high-embodiment of virtual agents improve learning, but these effects may not apply when there are negative social cues like low embodiment and machine voice. In our work, we want to investigate the role of system's voice (synthesized vs. human voice) in learning. More precisely, we look if the synthesized voice on Kompai robot impairs learning compared with the recorded human voice and if the embodiment of the robot improves learning or not when compared with a tablet. To the best of our knowledge, no work has already simultaneously focused on multimedia learning theory by using a robot and on the effects of stress and user's personality and gender on learning.

## 5.3 Case Study: Teaching Nutrition by using Multimedia with a Robot

Teaching using multimedia is a field where social robots can contribute in a great manner. Human-Robot Interaction (HRI) has shown improvement in learning compared to other electronic technologies, e.g., Leyzberg et al. (Leyzberg et al., 2012) show that the physical presence of a robot increases cognitive learning.

Social robots have been used before to teach topics related to health and nutrition. Kidd and Brezeal (Kidd and Brezeal, 2008) developed a robot that is used as coach for following a healthy diet. Short et al. (Short et al.,



2014) presented a robot for teaching children about nutrition through play and found promising results for the usage of SAR technologies for long-term one-on-one educational interventions for children.

In this context, and part of the EU Horizon2020 ENRICHME project, we investigated if a robot is capable of teaching elderly individuals on how to be healthy by having a healthy diet (by using speech and visual information). Nevertheless, before starting working with the final target population, the elderly, there are some relevant aspects that can influence the multimedia learning and that need to be studied in the field of social robotics.

### 5.3.1 Multimedia Learning Scenario

A multimedia presentation (of a 8 minutes duration and a total of 10 slides) using a web application of how to be healthy by having a healthy diet was presented to each participant by using different embodiment (a tablet or a robot) (as it can be seen in Figure 5.1). At the beginning of the experiment the participant was informed about the final goal of the project, which is using the system for teaching the participants (potentially the elderly) on how to be healthy by having a good nutrition. Afterwards, the presentation on the robot or tablet started with a brief explanation of the topic and the instructions. The participant had the choice to repeat the speech of each slide, go back to the previous slide, or go to the next slide. These options are provided in order to facilitate the learning to the pace of each participant. At the end of the presentation, the participant completed a test with 7 questions related to the information provided during the presentation, for which they had opened time to complete it, and he/she gets his/her score and an encouragement for the next time session. The participants also completed the Big 5 personality test (Goldberg, 1990) in order to determine their personality traits.

### 5.3.2 Multimedia design

The implementation of the user interface was done in a web application developed in HTML and javascript following the guide proposed by (Mayer, 2014b) in the Multimedia Learning Theory. It mainly consisted in the usage of representative images related to the speech of the presentation, few words on each slide, words and images close in space and meaning and buttons for repeating, going back, and forward through the slides. One of the slides used on this experiment is shown in Figure 5.2.

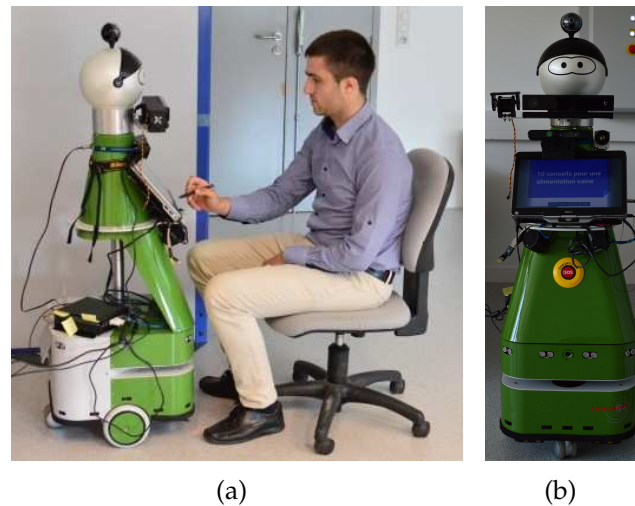


FIGURE 5.1: a) Multimedia Learning using a Kompai Robot to show a multimedia presentation. b) Kompai robot

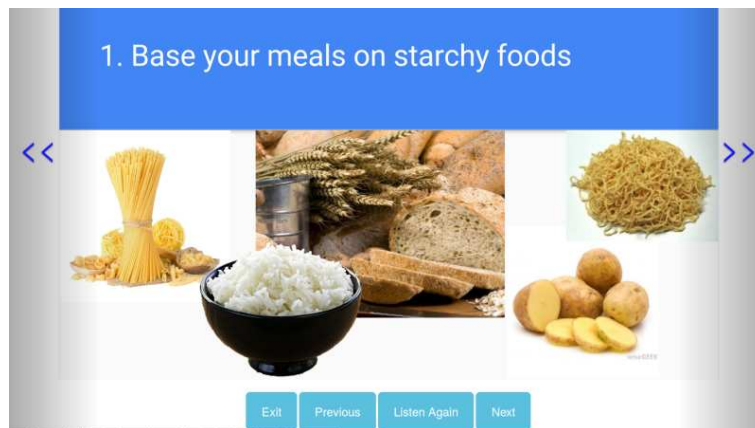


FIGURE 5.2: Multimedia design used on our experiment

### 5.3.3 Conditions

45 persons between 21 and 64 years, 24 males and 21 females, students and employees of an academic French institution (ENSTA ParisTech) took part in the experiment.

The participants were randomly divided in 4 groups according to our 4 conditions, using a robot (R) vs. a tablet (T), and synthesized voice (SV) vs. human voice (HV):

1. Robot and synthesized voice (R-SV): 5 male and 7 female participants.
2. Robot and human voice (R-HV): 7 male and 5 female participants.
3. Tablet and synthesized voice (T-SV): 6 male and 5 female participants.
4. Tablet and human voice (T-HV): 6 male and 4 female participants.

The robot used in our experiments is a Kompai robot, a robot developed by RoboSoft robotics company (currently Kompai robotics) as a home care system. It included a tablet PC where the multimedia information was presented (this computer was also used as tablet in the conditions 2 and 4). The synthesized voice was generated with the MaryTTS (Schröder and Trouvain, 2003) software using a French male voice. The human voice was recorded by a native French male person.

### 5.3.4 Hypotheses

Based on the literature, our hypotheses are as follows:

- H1. Human voice is better than synthesized voice for multimedia learning.
- H2. Robot embodiment is better than the usage of a tablet for multimedia learning.
- H3. Robot embodiment and synthesized voice is more stressful for the users than a tablet and human voice.
- H4. Neuroticism personality trait is positively related with the test score of the multimedia learning.
- H5. Stress will be negative related with time to perform the test and time will be negative related with the score on the test.

### 5.3.5 Post-experiment Questionnaires

Two post-experiment questionnaires were completed by the participants. In the first one, the participants provided some feedback on the experiment. The second one aimed at getting the participants' personality traits by using the Big 5 Personality test (Goldberg, 1990). These questionnaires were applied on another computer in order to avoid bias.

The first questionnaire (7 items) is presented in Table 5.1. The second questionnaire is the Big 5 personality test (45 items).

### 5.3.6 Image Analysis

Participants were recorded from front-face point of view using 2 cameras, an Asus camera, which recorded RGB-D images, and an Optris infrared camera, which recorded infrared images to analyze temperature variation.

Faces were detected using the Dlib toolkit (King, 2009) from both images. Moreover, from the RGB-D images the Action Units (AU) (Ekman and Friesen, 1977) corresponding to the mouth, nose, forehead, and nose-tip of the participants were extracted and three different emotions were detected (Biehl et al., 1997): Happiness, Sadness, and Surprise with the purpose of analyzing some of the emotions of the participants during the learning session. From the infrared images the nose-tip region was obtained and a butterworth low-pass filter with the method proposed in (Yu et al., 1999) for estimating the optimum cutoff frequency was applied to the sequence of images. The detections of the respiration rate and heart rate were done using systems developed on our laboratory, based on the works on several related works (Chon, Dash, and Ju, 2009) (Poh, McDuff, and Picard, 2010) (Leonard et al., 2003) (Laure, 2012).

### 5.3.7 Stress Analysis

Based on a review of studies using thermal images for measure user stress (Ioannou, Gallese, and Merla, 2014), it was observed that users' stress is correlated with a decrease in the temperature of the nose.

Thermal infrared imaging, takes advantages of the body's naturally emitted thermal irradiation. This method allows cutaneous temperature recordings to be measured noninvasively and contact free. The temperature of our bodies are generated by the autonomic nervous system, which controls many subsystems (i.e. heart rate, breathing, perspiration, respiration) that provide grounds for observations of emotional inferences.

TABLE 5.1: Post-Experiment Questionnaire

- Q1 Did you find this information useful?  
Choose a score from 1 (Not at all) to 5 (Very much)
- Q2 Were you aware of all these health tips?  
Choose a score from 1 (Not at all) to 5 (Very much)
- Q3 Did you find the audio information accompanying the slides helpful and clear? Yes/No
- Q4 Was the audio sufficiently loud? Yes/No
- Q5 Was the audio understandable? Yes/No
- Q6 Was the verbal information sufficiently rich in details?  
Choose a score from 1(Not at all) to 5 (Very much)
- Q7 Did you like the male voice? Yes/No

In (Ioannou, Gallese, and Merla, 2014) a review of Stress and Thermal image analysis is presented. Thermal imaging has been used to assess affective training times, in such work during the first trials, nose temperatures were lower as a sign of task difficulty. Another study assessed mental workload on professional drivers, where mental workload seemed to decrease the temperature of the nose, which dropped  $0.55^{\circ}$  C below baseline during a simulated city drive.

The temperature of the room where we realized the experiments was stable over the experiments (about  $19 \pm 0.5$  degrees), then this was not a factor for changes on the temperatures of the participants' faces.

## 5.4 Results and Discussion

The parameters used to evaluate the learning of the participants were the results of participants' good answers on the test after the multimedia session and the time they took to complete it. These two parameters are the dependent variables. As independent variables were taken the 4 conditions explained in the experimental design setup section (robot and synthesized voice, robot and human voice, tablet and synthesized voice, and tablet and human voice), the gender of the participants, and the five personality traits (Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism). The personality traits were categorized as high (value  $> 3$ ) and low (value  $\leq 3$ ). A Shapiro test was applied to verify the normality of the data.

### 5.4.1 Hypothesis 1: Human voice

A multifactor ANOVA ( $n = 45$ ) having performance time as dependent variable and embodiment (robot, tablet), voice (human, synthesized), and gender (male, female) as independent variables gave us insight into the interaction between system embodiment and voice, and system embodiment and gender. Analyzing the same independent variables with good answer scores as dependent variable showed no significant interactions. We also divided the data by gender and we found a significant interaction between performance time as dependent variable and embodiment and voice as independent variables on male participants ( $F[1, 20] = 7.0451, p = 0.01522$ ). Moreover, we found a significant interaction between performance time and voice in the conditions with the robot ( $F[1, 10] = 8.571, p = 0.0151$ ) for male participants.

TABLE 5.2: Male participants performed better in time on the test on the human voice condition on the robot

| Human voice |         | Synthesized voice |         |
|-------------|---------|-------------------|---------|
| Mean (secs) | std dev | Mean (secs)       | std dev |
| 80.2857     | 21.2893 | 120.6000          | 26.5103 |

We applied a pairwise t-test for these variables and the result shows a significant difference with  $p = 0.015$  between human voice and synthesized voice for male participants ( $n = 12$ ) in the conditions with the robot. Male participants in the human voice conditions finished the test quicker than male participants in the synthesized voice conditions, the means and STD are shown in Table 5.2 and illustrated in Figure 5.3.

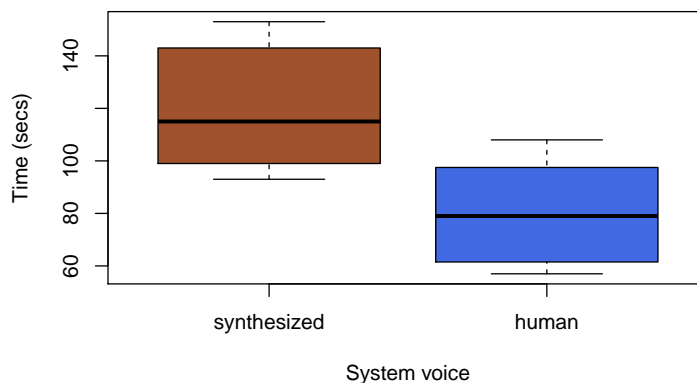


FIGURE 5.3: Male participants got better time performance in the human voice condition with the robot (R-HV)

### 5.4.2 Hypothesis 2: Robot embodiment and Learning

Similarly to the analysis of Hypothesis 1, a series of multifactor ANOVA were applied having time performance and answers as dependent variables, and conditions, personality traits, and gender of the participants as independent variables. No statistically significant difference could be observed between these variables.

TABLE 5.3: Mean and STD of temperature variation of nose-tip region of the participants in the 4 conditions, The mean in Condition 1 (robot and synthesized voice) presents a decrease on temperature, meaning higher stress.

| Condition | Mean (secs) | std dev |
|-----------|-------------|---------|
| 1:R-SV    | -0.8260     | 0.6724  |
| 2:R-HV    | 0.5942      | 1.4248  |
| 3:T-SV    | 0.5966      | 0.9771  |
| 4:T-HV    | 0.8866      | 0.8550  |

### 5.4.3 Hypothesis 3: Robot embodiment and Stress

An ANOVA test with nose-tip temperature variation as dependent variable and condition as independent variable showed a significant interaction ( $F[1, 19] = 4.7963, p = 0.0412$ ) between condition 1 (R-SV) and variation of temperature of the nose-tip region of male participants and the rest of the conditions. A pairwise t-test revealed a difference with  $p = 0.040$  between condition 1 (R-SV) and condition 2 (R-HV),  $p = 0.046$  between condition 1 (R-SV) and condition 3 (T-SV), and  $p = 0.046$  between condition 1 (R-SV) and condition 4 (T-HV). The mean of the temperature variation of the nose region of male participants in condition 1 (R-SV) showed a decrease in temperature (meaning increase of stress), while the others conditions showed an increase in temperature. The means and standard deviation are shown in Table 5.3, and illustrated in Figure 5.4.

There were no significant differences of temperature variations on the female groups.

### 5.4.4 Hypothesis 4: Stress, and time and test score

A negative correlation with value of  $-0.6287$  with  $p = 0.0164$  using a Pearson correlation test was found between the temperature variation on the nose-tip region of the participants ( $n = 45$ ) and the time they took to complete the test, a higher time is linked with a decrease in temperature (see Figure 5.7), this correlation can be seen in Figure 5.5. Another negative correlation with value of  $-0.3754$  with  $p = 0.0110$  using the same test was found between the score of the participants on the test and the performance time, a higher score is linked with a quicker performance time to complete the test. This correlation is shown in Figure 5.6, the means and STD are shown in Table 5.4.

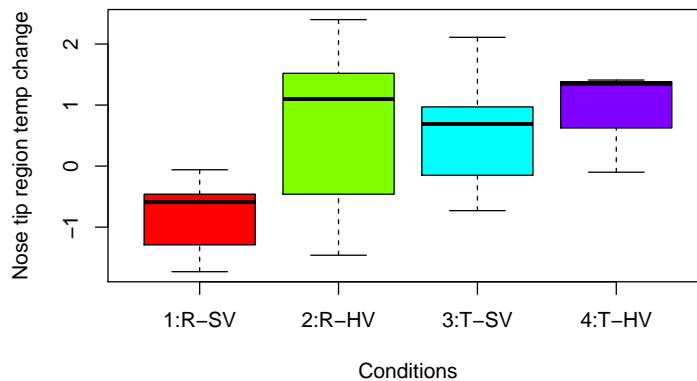


FIGURE 5.4: Temperature of the nose-tip region of the participants decreased more in Condition 1 (robot and synthesized voice) than in the others conditions, meaning more stress for the participants in Condition 1.

TABLE 5.4: Mean and STD of time performed (in seconds) by the participants on the test grouped by score (good answers) on the test.

| Score | Mean (secs) | std dev |
|-------|-------------|---------|
| 2     | 122.66      | 27.31   |
| 3     | 102.00      | 26.46   |
| 4     | 83.83       | 23.71   |
| 5     | 82.75       | 30.31   |
| 6     | 75.50       | 12.45   |
| 7     | 86.00       | 39.59   |

### 5.4.5 Hypothesis 5: Neuroticism

A multifactor ANOVA with good answers as dependent variable and the 4 conditions, gender, and the five personality traits as independent variables was applied to validate this hypothesis. A statistically significant interaction between gender and Neuroticism ( $F[1, 16] = 5.9745, p = 0.0264$ ) was found. Following this interaction, we divided the data by gender, and a significant relation with ( $F[1, 22] = 5.0802, p = 0.0345$ ) was found. Male participants with high level of Neuroticism got a better score on the test than male participants with low level of Neuroticism, the result of this ANOVA is shown in Table 5.5 and the plot of the scores of male participants grouped by level of Neuroticism is shown in Figure 5.8.



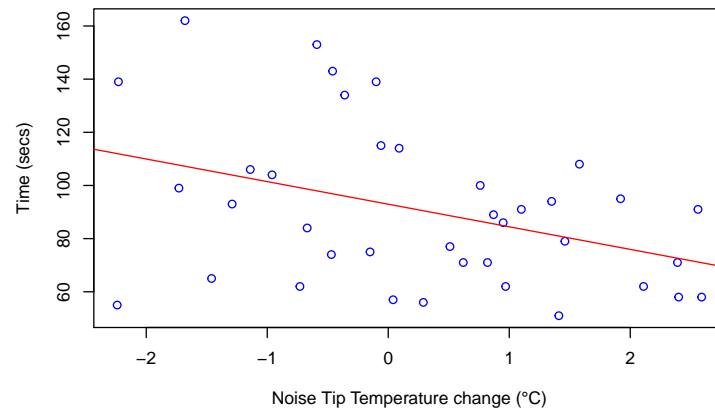


FIGURE 5.5: Negative correlation between temperature of the nose-tip region of the participants and performed time of participants on the test, which shows that stress is linked with a higher time performing the test.

TABLE 5.5: Male participants with high level of Neuroticism got a better score on the test (good answers) than male participants with low level of Neuroticism

| High Neuroticism |         | Low Neuroticism |         |        |  |  |
|------------------|---------|-----------------|---------|--------|--|--|
| Mean             | std dev | Mean            | std dev |        |  |  |
| 5.3333           | 0.5163  | 4.1111          | 1.2782  |        |  |  |
| Sum sq           | Mean sq | Df              | F       | p      |  |  |
| 6.7222           | 6.7222  | 1               | 5.0802  | 0.0345 |  |  |

#### 5.4.6 Questionnaire for feedback

We analyzed the post-experiment questionnaire providing feedback on the experiment (questionnaire presented in Appendix A.6). We applied an ANOVA test with the questions as dependent variable and gender as independent variable. We found a relation between Question 1 (the perceived usefulness of the information) and the gender of the participants ( $F[1, 45] = 6.3015$ ,  $p = 0.0159$ ). Female participants perceived the nutrition information as more useful than male participants. The results of the one-way ANOVA are presented in Table 5.6 and the perceived usefulness of the information grouped by gender is illustrated in Figure 5.9.

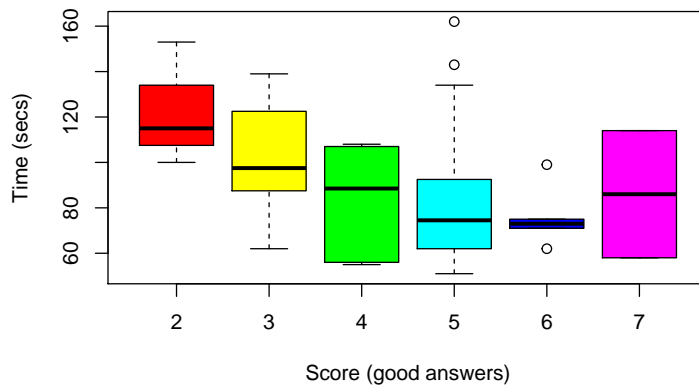


FIGURE 5.6: Mean and SD of the performed time grouped by score of the test of the participants, lower score is linked with higher time performing the test.

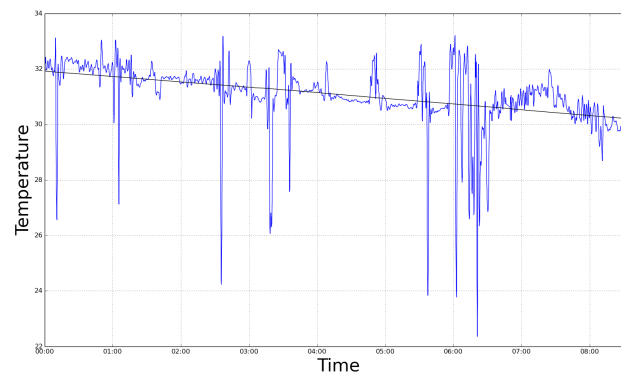


FIGURE 5.7: Temperature (Celsius) decrease in the nose-tip region of one participant (Time in minutes)

### 5.4.7 Discussion

The results found in this work validated most of the hypotheses we formulated.

Hypothesis 1 was validated but only with male participants. Male participants obtained a better score on the test in the condition with the robot with the human voice (R-HV) than in the condition with the robot with the synthesized voice (R-SV). This difference was not found in the conditions with the tablet. This could suggest that male participants were more relaxed with the robot having a human voice, then it could be important for robots to have a natural human voice instead of a robotic one.

Hypothesis 2 was not validated. This can be explained by the multimedia learning theory (Mayer, 2002) because of the synthesized voice used in

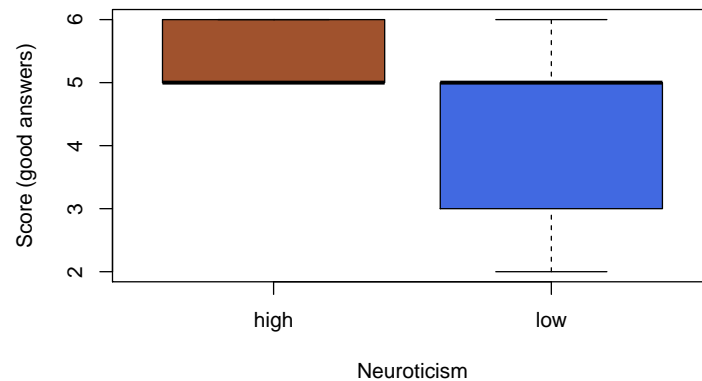


FIGURE 5.8: Male participants with high level of Neuroticism got better score (good answers on the test) performance than male participants with low level of Neuroticism

TABLE 5.6: Female participants perceived the nutrition information as more useful than male participants (on a 7-point Likert scale)

| Female   |         | Male   |         |
|----------|---------|--------|---------|
| Mean     | std dev | Mean   | std dev |
| 4.047619 | 0.9206  | 3.3750 | 0.8753  |

| Sum sq | Mean sq | Df | F      | p       |
|--------|---------|----|--------|---------|
| 5.067  | 5.0671  | 1  | 6.3013 | 0.01591 |

Condition 1 and also for the low level of embodiment of our robot that lacks of arms, legs, and facial expressions. A more anthropomorphic robot could potentially have a better impact on users' learning.

Hypothesis 3 was validated. The condition with the robot and synthesized voice (R-SV) generated more stress in the participants than the condition with the robot and human voice (R-HV) and the conditions with the tablet, this was shown by a decrease in temperature in the nose-tip region.

Hypothesis 4 was also validated. Stress showed a negative correlation with the performed time of the participants on the test, and time showed also a negative correlation with the score obtained. This means that when users got stressed they tended to spend more time on the test and their learning (score) tended to be poor.

Hypothesis 5 was validated, but only with male participants. High Neuroticism male participants performed better on the test than low Neuroticism

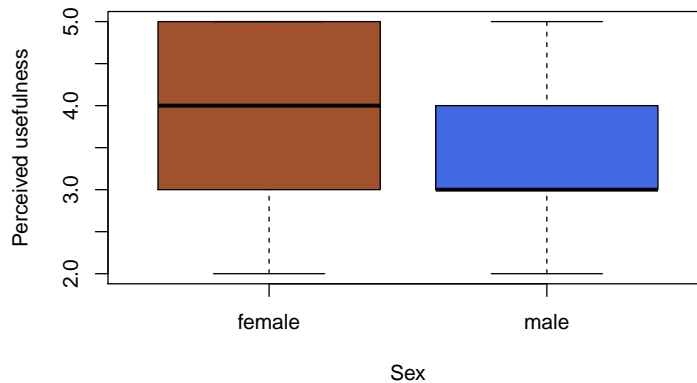


FIGURE 5.9: Female participants perceived the information on nutrition as more useful than male participants (on a 7-point Likert scale)

male participants. Then, we think that it is important to take this in consideration when designing Human-Robot Interaction scenarios, specially in learning contexts.

## 5.5 Contributions and Conclusion

In this chapter, we investigated the role of embodiment (robot vs. tablet), and system's voice (synthesized voice vs. human voice) in a teaching nutrition and healthy eating scenario using multimedia.

The main contribution of this chapter is the simultaneous study of multimedia learning theory by using a robot and the effects of stress and user's personality and gender on learning. Also, we developed a Multimedia presentation in HTML and javascript for Teaching Healthy Nutrition, presented to the participants of the experiments using a Kompai robot and a tablet computer.

The results showed an increase of stress in the condition where the robot and synthesized voice (R-SV) was used, which means a negative correlation with performance on learning. Robots can be helpful in assistive tasks like the one proposed in this paper, but we need to be aware of the stress caused to the users, in the case of the teaching by using multimedia this could be done by lowering the learning time in the first sessions.

Furthermore, we need to pay more attention to users with high level of Neuroticism, who scored better on the test, but probably this was due to their

anxiety, other negative effect that could be generated by the robot's presence.

Female participants did not show any significant difference on their performance under the 4 different conditions as male participants did, we suspect that this is due to their interest in learning about the learning topic proposed in the experiment.

The work done on this chapter, was presented in the International Conference on Humanoid Robots (Humanoids), Cancun, Mexico, 2016, (Cruz-Maya and Tapus, 2016b).

In the next chapter, we present our framework, implemented on a Pepper robot, for learning user preferences based on personality and gender, then we continue analyzing the stress on the users in Human-Robot Interaction in the following chapters.

## Chapter 6

# Adapting a Robot Behavior to Personality Preferences

Robots are expected to interact with people in their everyday activities, and robots should do it in a way that does not increment the level of stress or anxiety of the users. Therefore, robots should learn the preferences of their users. Having a memory system that remembers past events and using it to predict the outcome of the robot's behavior is a useful feature that robots should possess.

Research in social robotics has shown that robots with emotions and personality are considered to have more believable behavior and are preferred over robots that lack these features (Kröse et al., 2003). Furthermore, emotions have proved to be important for cognition, and some models have been designed to represent the emotions and their role on cognition. One of them is the OCC model (Ortony, Clore, and Collins, 1990), which has been used in virtual agents (Becker-Asano and Wachsmuth, 2010) and in some robots (Kröse et al., 2003) to embody them with emotions and make their behavior more appealing to the users. More details were given in Chapter 2.

In the field of Social Psychology, it is widely known that individuals with the same personality have similar preferences. Nevertheless, there exists two theories that seem opposite one another. One of them is called the Similarity Attraction Theory (Byrne, Griffitt, and Stefaniak, 1967), which states that people are attracted by other people with similar personality. The second one is called Complementary Needs Theory (Winch, Ktsanes, and Ktsanes, 1954), which states that people are attracted by other people with different personality. Both theories have been supported by works in social robotics. In (Lee et al., 2006), participants enjoyed interacting with an AIBO robot when the robot's personality was complementary to their own preferences. In (Joosse et al., 2013), similarity attraction theory was supported when the robot was a tour guide, and the complementary theory was supported when the robot

was a cleaner.

Using an adaptive behavior could be useful to predict the preferences of individuals, when there are no past interactions between them and the robot, if the robot has interacted with other people in similar situations. Instead of having assumptions about any of these theories, the robot would create its own model of user's preferences based on previous experiences. This can be used to model different preferences for different tasks.

There exist many works where a robot is trained from several demonstrations and learn to generate the desired behavior (Argall et al., 2009). However, there are only a few works with robots learning online, through interactions with their users, which could be a better form of learning due to the constantly changing nature of the human's preferences.

In a previous work, an assistive therapist robot that adjusted its behavior parameters with respect to the personality and performance of the user was presented (Tapus, Tapus, and Matarić, 2010). A humanoid torso robot mounted on a mobile platform was used with an algorithm based on a policy gradient reinforcement learning for the adaptation. Personalizing a robot by learning the preferences of their users has also been approached before in (Mason and Lopes, 2011). The authors developed a robotic system that interacts with the user, and through repeated interactions, adapts to the user. They used a beta regression classifier for learning and generalization of the task, they tested their system with a "room cleaning" scenario in a simplified world, where a small robot with a holonomic base was navigating and transporting blocks to the desired position of the users. Another adaptive learning algorithm based on user's feedback for human-robot interaction is proposed in (Karami, Sehaba, and Encelle, 2014). The authors used a Markov Decision Process (MDP) and learning adaptation rules to allow the robot to adapt to different situations and personalize its behavior.

A recent work on engagement and its relation to personality in human robot interaction, is presented in (Salam et al., 2017). They propose an automatic analysis of users' personality in a triadic human-human-robot interaction. The analysis is used to predict the personality of the users, and this information is used as an input for the engagement classification system. They focus on the concept of "group engagement" and found better engagement when the participants and the robot were extroverted, and the worst results were obtained when all were introverted.

Using information about the interaction of the robots with the users so as

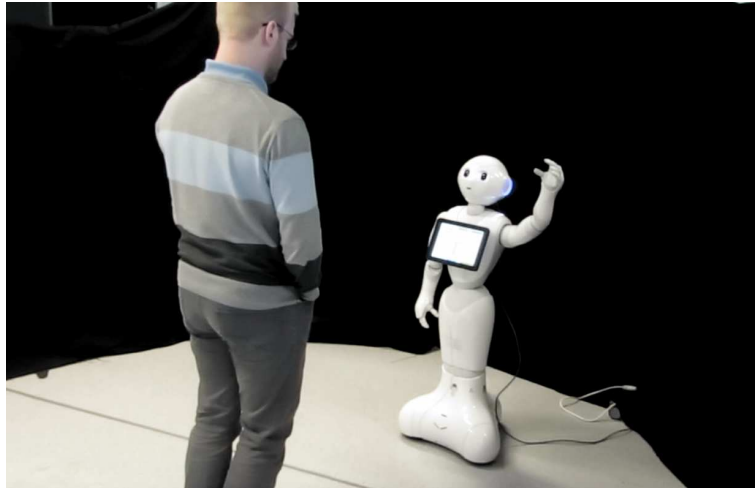


FIGURE 6.1: Interaction scenario with a Pepper Robot

to personalize the interaction over time, allows for more successful and natural human-robot interactions (Leyzberg, Spaulding, and Scassellati, 2014). We propose a framework that includes an Adapted Episodic Memory-like system, which is extended with an Emotion system based on the OCC Model to update the intensity of the memories of past interactions with respect to the user's feedback. This framework has not only to remember the preferences of specific users, but also to generate behaviors for new users based on their personalities. The difference of our proposed model and other existing research works, is that it can generate a specific behavior for each user based on previous interactions, and also, it can generate personality-based behaviors, using the interactions with different users instead of preset information.

In this chapter, we describe our proposed framework for an adaptive robot behavior, as well as an experiment divided in two parts. In the first part, the model of the robot's behavior is created. A group of participants interacts with the robot three times, in different days each time, and they specify their preferences for three parameters defining the robot's behavior in a close interaction (as shown in Fig. 6.1). The preferences are saved individually for each user and also grouped by personality and gender. In the second part of the experiment, the current state of the robot's memory is used to generate the saved behavior to other group of participants with respect to their personality and gender.

In the next section, we present the chosen parameters for our model of robot behavior, in section 6.2, we depict our framework on how to learn user preferences of a robot behavior, in section 6.3, we describe our experiment and the results we got from it. The contributions and conclusion of this chapter are summarized in section 6.6.



## 6.1 Choosing the Features to Create the Model

We assume that the robot has a priori information about the user, including the gender and personality of the user.

In our previous chapters, we explained based on the results of some experiments the necessity and the importance of personality and gender in human-robot interactions. Considering this, we decided to include these user profile parameters in our model.

It was chosen to express the behavior of the robot through three parameters configured by the user: personal distance, gesture amplitude, and gesture speed. These parameters were selected because of their strong link and correlation with the extroversion/introversion personality trait. It is well known that extroverted individuals tend to do wider and faster gestures (Knapp, Hall, and Horgan, 2013) (Lippa, 1998), and also that they prefer closer distances than introverted individuals (Williams, 1971). The gesture used was a wave of the left arm of the robot, when the robot was greeting the user. These three parameters (personal distance, gesture amplitude, and gesture speed) were also included in the model for the reasons mentioned above.

## 6.2 Learning a Model of Users Preferences of Robot Behavior

The high level framework used here was introduced in Chapter 3, where the OCC Model was used to generate predefined behaviors based on the performance of the user. In this chapter, the model of emotions is used to regulate the intensities of the memories saved in the Episodic-Memory, based on past interactions and new user's feedback.

The OCC model of emotions, lacks the specification of the agent's memory and how the agent's behaviors are modulated with the use of emotions. The memory system combined with the emotions has been adopted in (Leconte, Ferland, and Michaud, 2016), where an Episodic-like Memory System (EM) with emotions regulating the intensities of memories on a robot is used. The EM has the advantage of learning online through experience and the capacity to predict expected events based on past experiences. Here, we propose the usage of the OCC model to synthesize the emotion that regulates the intensities of the memories saved in the EM.

The purpose of the framework is to remember users' preferences with respect to a certain robot's behavior that is saved in the Episodic-like Memory (EM). This allows the memories to be in constant variability of recall, more frequent events have a higher recallability. The intensity with which these events are saved depends on the users' feedback and the emotion generated by the Emotion System.

The process of the proposed algorithm is showed in Figure 6.2. It is started by a search of the user's preferences for a specific behavior of the robot. If there exist information about this in the EM, then the behavior is performed with the preferences of the user, if there is no information about the user's preferences, then a search based on the personality and the gender of the user is done. The behavior based on this information, if there is any, is performed, otherwise a default behavior is executed. The user can modify the behavior of the robot by changing the parameters defining robot's behavior (i.e., personal distance, gesture amplitude, gesture speed) and this is done by voice command. After the user finished with the modifications, the parameters are updated with a new weight, rating them with respect to the new user's preferred parameters. The OCC model is used to calculate this weight using the emotion of Hope, which according to this model, is an emotion belonging to the category Consequences of Events having a prospect relevant.

### 6.2.1 Configuring the Episodic Memory

The EM-ART model (Wang et al., 2012) is made of three layers: Input, Events, and Episodes. Our framework uses the AEM-ART (Adapted Episodic-Like Memory Adaptive Resonance Theory) implementation presented in (Leconte, Ferland, and Michaud, 2016). The input layer is categorized by channels, each channel containing different elements that are called categories. Also, each category has a channel relevance and activation value, the relevance allows the system to save general information in that channel when its value is 0, and save specific information when its value is 1. The activation value is used to match a search depending on the channel relevance.

We are saving the information in two types of episodes, one of them is used to save the specific preferences of the users, and the other one is used to save the preferences grouped by personality type (extroversion/introversion) and gender (male/female).

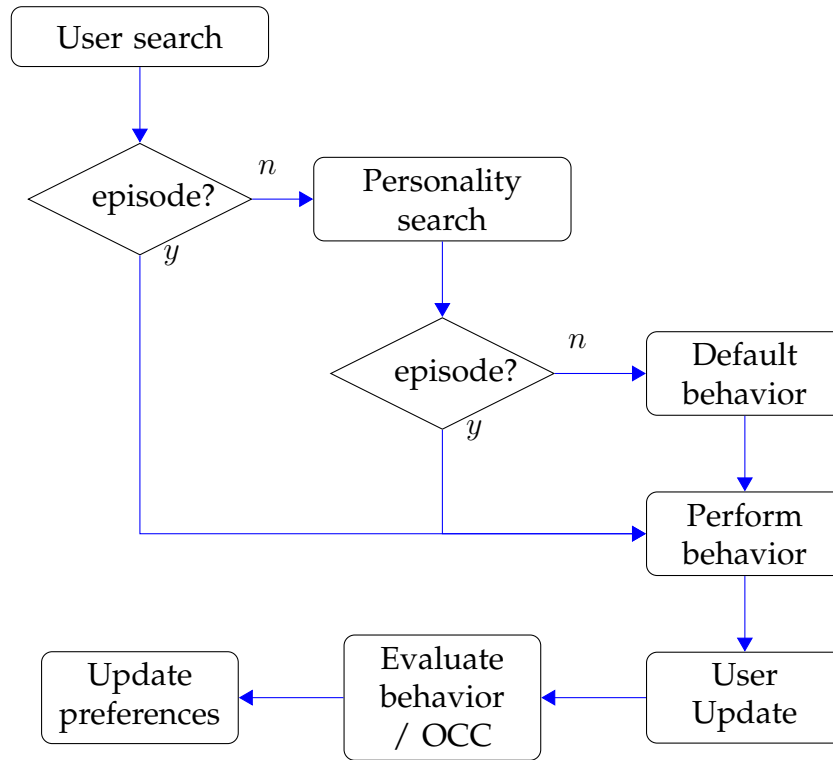


FIGURE 6.2: Process of the proposed framework

### Episodes with specific information

For the episodes containing specific user's preferences we used the following channels in the input layer:

- User: Category = Name of the user (unique), channel relevance = 1.0 (max), activation value = 1.0 (max).
- Order: Used to facilitate the memory search, Category = 1: search, 2: saved preferences, channel relevance = 1.0, activation value = 1.0
- Distance: Preferred distance between the robot and the user, given in meters, Category = [0.4,0.6,0.8,1.0,1.2], channel relevance = 1.0, activation value = 1.0
- Amplitude: Preferred amplitude of the gesture of the robot's arm, given in percentage of the total amplitude, Category = [0.2,0.4,0.6,0.8,1.0], channel relevance = 1.0, activation value = 1.0
- Speed: Preferred speed of the gesture of the robot's arm, given in percentage of the total speed, Category = [0.2,0.4,0.6,0.8,1.0], channel relevance = 1.0, activation value = 1.0

- Emotion: Emotion of Hope generated using the OCC Model, Category = 'hope', channel relevance = 1.0 (max), activation value between 0 and 1.

The search is done with the channels of the User, Order, and Emotion. The Emotion is used to decrease the importance of past preferences (explained in Section 6.2.2). In this work, we setup the memory to always retrieve the last Episode of the user (Emotion at max. value), meaning his/her last preferences. This gives us episodes with two events, where the first event is used for the search, and the second event contains all the channels described above. A new episode is created for each new user or new preferences of a known user.

### Episodes with personality/gender information

For the episodes containing information grouped by personality and gender, we used the following channels in the input layer:

- Personality: Category = Personality of the user (Extrovert/Introvert), channel relevance = 1.0 (max), activation value = 1.0 (max).
- Gender: Category = Gender of the user (Male/Female), channel relevance = 1.0, activation value = 1.0
- Order: Used to facilitate the memory search, Category = 1: search, 2: saved preferences, channel relevance = 1.0, activation value = 1.0
- Distance: Preferred distance between the robot and the user, given in meters, Category = [0.4,0.6,0.8,1.0,1.2], channel relevance = 0.0, activation value between 0 and 1, generated using the emotion system.
- Amplitude: Preferred amplitude of the gesture of the robot's arm, in percentage of the total amplitude, Category = [0.2,0.4,0.6,0.8,1.0], channel relevance = 0.0, activation value = between 0 and 1, generated using the emotion system.
- Speed: Preferred speed of the gesture of the robot's arm, in percentage of the total speed, Category = [0.2,0.4,0.6,0.8,1.0], channel relevance = 0.0, activation value = between 0 and 1, generated using the emotion system.

The episodes generated using this channel configuration contain two events, one for the memory search (Personality, Gender, Order) and the other one

with all the channels presented above. The channels of Distance, Amplitude, and Speed (parameters' channels) are set up with a channel relevance of 0 in order to save general information on them, grouped by personality and gender, which were set up with a channel relevance of 1. The activation value of each Category in the parameters' channels are updated each time a user save his/her preferences, increasing the activation of preferred parameters with a value in an empirically calculated range from 0 to 0.2. This value depends on the emotion generated by the emotion system. The activation of each Category of non preferred parameter is decreased by a factor of 5% of its current value. This is done with the purpose of slowly forgetting not frequently chosen parameters.

### 6.2.2 Adapting the OCC Model

The OCC Model (Ortony, Clore, and Collins, 1990), described in more detail in chapter 2, is a model commonly used in virtual agents to synthesize emotions, it has 22 emotions and they are divided in three categories: *Aspect of Objects*, *Action of Agents*, and *Consequences of Events*. In this work, we focused on the category of Consequences of Events for Self, especially in the emotion of Hope. This can improve the Adapted-Episodic-like Memory system rating the memories with higher activation values for events more liked by the users. We use the Hope emotion because it is a prospect based emotion, unlike emotions of joy or distress which are well-being emotions having prospects irrelevant or others emotions which are based on Consequences for Others.

We have two types of episodes, one for specific user's preferences and one for personality/gender preferences. We generate the emotion of Hope for each type of episodes.

#### Emotion for episodes with specific information

For the type of episodes with information about specific user's preferences, each time a search is done in the memory system, an emotion of Hope is generated. We used 4 global variables of the OCC model and 2 local variables, all of them normalized with values between 0 and 1.

The global variables are:

- Sense of Reality (*SoR*): value = 0.75, because this emotion is based on the memories of a specific user.

- Proximity (*Prox*): value= 1, because our scenario presents a close interaction between the robot and the user,
- Unexpectedness (*Un*): value =  $1 - EpisodeActivation$  (memory system)
- Arousal (*Ar*): value = 0.5, in order to set a neutral value for this variable.

The global variables were combined computing the mean of all of them (Eq. 6.1).

$$GlobalVar = (SoR + Prox + Un + Ar)/4 \quad (6.1)$$

The values of the local variables (*Likelihood* and *Desirability*) are computed as follows:

$$Likelihood = \frac{\sum_{i=1}^n ActivationChannel_i}{n} \quad (6.2)$$

where  $n$  is the number of parameters' channels (three in this case)

$$Desirability = 1 \quad (6.3)$$

The value of *Desirability* was set to 1, because there is only one objective in the task performed by the robot.

In the OCC model, the potential of the emotion is obtained by combining the global variables with the local variables. Each emotion has also a threshold to discard emotions with low potential. In this work, the emotion potential is computed as shown in Eq. 6.4. The threshold of the emotion was set to 0 to allow an intensity of the emotion ranging from 0 to 1.

$$EmP = (Des * 0.7 + GlobalVar * 0.3) * Lk \quad (6.4)$$

where *EmP* is the Emotion Potential, *Des* is the Desirability, *GlobalVar* are calculated using the Equation 6.1, and *Lk* is the Likelihood.

After the user gives the feedback to the robot, there are two possible emotions that are consequence of the emotion of Hope. These emotions are Satisfaction Confirmed and Disappointment. Satisfaction confirmed happens if the user's preferences remain unchanged. Then, the synthesized emotion of Hope is assigned to the preferred parameter. Disappointment happens if the user's preferences are different than the remembered preferences. Then, the emotion assigned to the preferred parameter is  $1 - Hope$ . The final emotion is the average of all the emotions of each parameter, which is used as an activation value in the category of Hope in the emotion channel of the memory

system. New events, which are the preferences of the user, are set with a high level of emotion in order to be easy remembered.

### Emotion for episodes with personality/gender information

For the type of episodes with information about personality / gender, we used the same variables, changing the Sense of reality to 0.5, because the memory retrieved is composed by several users. For the same reason, the values of the Desirability and Likelihood need to be computed based on the information in the memory system, as well as a prediction of the preferred parameters.

The predicted parameters are computed by using the information contained in the Episodic-like Memory as follows:

$$Param_k = \frac{\sum_{i=1}^n Ch_k[Cat_i] * Ch_k[Act_i]}{\sum_{i=1}^n Ch_k[Act_i]} \quad (6.5)$$

where  $k$  is the channel of the predicted parameter,  $Cat_i$  is the Category  $i$  of the channel  $k$ , and  $Act_i$  is the activation  $i$  of the channel  $k$ . Each  $Param_k$  is rounded to a value multiple of 0.2 in order to discretize them. When there are no preferences saved in memory, the predicted value is set to 0.6.  $Param_k$  is associated with an activation value  $Param_k[Act]$ , corresponding with the category with the same value of the channel  $k$ .

The likelihood of each predicted parameter is:

$$lk_k = \frac{Param_k[Act]}{\sum_{i=1}^n Ch_k[Act_i]} \quad (6.6)$$

where  $k$  is the channel of the predicted parameter, and  $n$  is the number of categories in the channel  $k$  and  $Act_i$  is the Activation  $i$  of the channel  $k$ .

The local variables were computed as follows:

$$Likelihood = \frac{\sum_{k=1}^n lk_k}{n} \quad (6.7)$$

$$Desirability = \frac{\sum_{i=1}^n Ch_i[Max(Act)]}{n} \quad (6.8)$$

where  $n$  is the number of parameter channels.

The emotion is computed as described above.

## 6.3 Case Study: Learning Users' Preferences and using them with New Users

The purpose of this work was to customize a robot's behavior to users' preferences. This learned behavior was shown to new users, using the information saved in the Episodic Memory to perform the behavior with the most common preferred parameters by individuals with the same gender and personality. For this reason, we did an experiment divided in two parts. The first part was done to test the Episodic-like Memory (EM) and the behavior of the robot, and to train a model of users' preferences based on personality and gender. The second part was done in order to test the models created by the EM. The behavior of the robot was expressed through three parameters configured by the user: personal distance, gesture amplitude, and gesture speed. We chose these parameters because of their link and correlation with the extroversion/introversion personality trait. It is well known that extroverted individuals tend to do wider and faster gestures (Knapp, Hall, and Horgan, 2013) (Lippa, 1998), and also prefer closer distances than introverted individuals (Williams, 1971). The gesture used was a wave of the left arm of the robot, when the robot was greeting the user.

### 6.3.1 Hypothesis

Remembering user's preferences is one of the basic capacities that personal robots should have, but these preferences should not be fixed over time. Robots should be able to change these parameters with respect to the preferences of the users. The inter-individual differences based on personality and gender need to be integrated and the robot's behaviors should best match the preferences of new users.

Our hypothesis is stated as follows:

H1. The robot's behavior generated after interactions with individuals of different personalities and genders will best match with the preferences of new users than by using fixed behaviors based on the theories of Similarity attraction or Complementarity attraction.

### 6.3.2 Robot Capabilities

The robot used was a Pepper robot, which has the capabilities of face detection and face tracking, voice recognition, and movement of the body and



head to track the user. These capabilities are provided by the NaoQI Framework. We used the Naoqi ROS driver to communicate with the Episodic-like Memory and Emotion systems that were located on an external computer.

## 6.4 Methods

### 6.4.1 Training the robot

In order to train our model based on personality and gender, 16 Participants were recruited to perform this experiment, 8 male and 8 female participants, with ages between 25 and 56 years old.

The experiment was done as follows. The participants were instructed to interact one by one with the robot in a dyadic interaction, the robot was able to recognize a list of voice commands (see below). Participants were standing in front of the robot. The robot greeted the participant with a hand wave and verbal greeting, "Hello, I'm learning about personality preferences for which I will interact with you for some minutes. You can modify three parameters of my behavior: personal distance, gesture's amplitude and gesture's speed". The robot listed the voice commands and showed them on the tablet mounted on its torso (see Fig.6.3). Then the participants were free to give the desired commands to modify the parameters of the robot. It was repeated 3 times for each participant in different days each time.

The voice commands and their purpose are as follows: (a) Show Commands: To show on the tablet the list of voice commands; (b) Modify distance: To modify the distance between the robot and the user; (c) Modify gesture: To modify the gesture's amplitude; (d) Modify Speed: To modify the gesture's speed; (e) Reduce: To reduce the chosen parameter; (f) Increase: To increase the chosen parameter; (g) Done: To finish the modifications; (h) Yes: To confirm the "Done" command; (i) No: To cancel the "Done" command. Each time the user said one of the commands to modify a parameter, one image was illustrated on the torso tablet that showed the robot and the current value of the parameter in terms of percentages for the speed and amplitude, and in meters for the distance. The used images are shown in Fig. 6.3. The distance had values in a range of 40 cm to 120 cm (as stated by Hall Hall, 1966). The minimum and maximum values for the amplitude of the wave of the robot's arm are shown in Table 9.1, a full schema of the joints and angles is shown in the documentation website<sup>1</sup> of the robot. The speed had values

<sup>1</sup>[http://doc.aldebaran.com/2-0/family/juliette\\_technical/joints\\_juliette.html](http://doc.aldebaran.com/2-0/family/juliette_technical/joints_juliette.html)

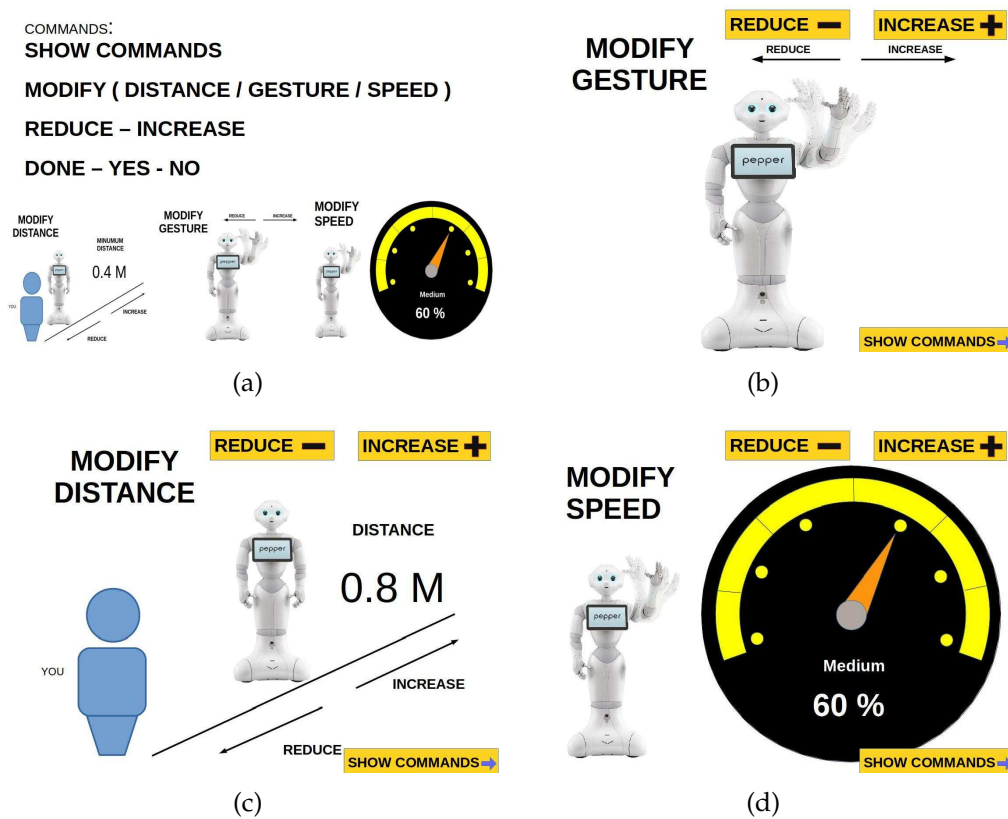


FIGURE 6.3: Images showed on the tablet of the robot. a) Image to show the voice commands, b) c) d) Images displayed when the user was modifying each parameter.

between 40% to 100% of the maximum speed provided by SoftBank Robotics, details of the motor of each joint are shown in the documentation website<sup>2</sup> of the robot. The robot performed the behavior each time the user said "increase" or "decrease" the chosen parameter. Learning is done after the first interaction for each user of each personality/gender group.

### 6.4.2 Pre-experiment Questionnaire

The participants were chosen with respect to their scores on a personality test (Big 5 Goldberg, 1990). The personality test was filled-in by the participants before the experiments. Individuals with a score  $\leq 3$  on a personality trait were considered in the low category of that specific personality trait. The training phase was done with 16 participants: 4 in each group (introverted/extroverted and male/female). The testing phase was done with 26 participants: 8 introverted males, 9 extroverted males, 4 introverted females, and 5 extroverted females.

<sup>2</sup>[http://doc.aldebaran.com/2-0/family/juliette\\_technical/motors\\_juliette.html](http://doc.aldebaran.com/2-0/family/juliette_technical/motors_juliette.html)

TABLE 6.1: Amplitude of the wave of the robot's arm

|                | Minimum          | Maximum         |
|----------------|------------------|-----------------|
| Shoulder Roll  | 40.1° to 42.4°   | 40.1° to 51.5°  |
| Shoulder Pitch | 68.75°           | 68.75°          |
| Elbow Roll     | -74.5° to -51.5° | -74.5° to -5.7° |
| Elbow Yaw      | 0°               | 0°              |
| Wrist Yaw      | 34.4°            | 34.4°           |

### 6.4.3 Post-Experiment Questionnaire - Training Phase

A post-experiment questionnaire (10 items) was applied to the participants that modified the parameters of the robot's behavior. The first 6 questions were designed to know if individuals preferred lower or higher values for the min and max parameters, and the other 4 questions were designed to know if individuals considered the parameters they chosen as appropriate, with answers on a 5 points Likert scale. Most of the participants did not like lower minimum values or higher values for the parameters of the robot's behavior. The percentages of the participants for the answers of the questions 1 to 6 are shown in Table 6.2. Also, most of the participants rated the chosen parameters as appropriate (4 on a scale from 1 to 5) in the questions 7 to 10 (as shown in Table 6.3). The final behavior was most of the times rated as neutral.

### 6.4.4 Testing of the model

In order to test our model based on personality and gender, 26 Participants were recruited to perform this experiment, 17 male and 9 female participants, with ages ranging from 20 to 47 years old. Participants taking part in the

TABLE 6.2: Answers of participants in the Training phase - Questions 1-6

|                  | Yes    | No     |
|------------------|--------|--------|
| Lower Distance   | 6.2 %  | 93.8 % |
| Higher Distance  | 37.5 % | 62.5 % |
| Lower Amplitude  | 25.0 % | 75.0 % |
| Higher Amplitude | 18.8 % | 81.2 % |
| Lower Speed      | 6.2 %  | 93.8 % |
| Higher Speed     | 43.8 % | 56.2 % |

training phase were not part of the testing group. We designed two robot behaviors based on the literature about introverts and extroverts, the values of our interaction parameters were chosen using the minimum and maximum values chosen by the participants in the training phase. The values of each parameter for each personality of the robot are shown in Table 6.4.

Each participant observed the robot performing the behavior generated by our model with respect to his/her personality and gender, the introverted behavior of the robot, and the extroverted behavior of the robot. The robot's behaviors were presented in a random order to each participant. At the end of each robot's behavior, the participant completed a questionnaire with three questions about his/her preferences about the three parameters to evaluate (distance/amplitude/speed). The answers were on a 5 points Likert scale, where 1 was "too close/narrow/slow" for the distance/amplitude/speed respectively, "3" was "appropriate", and 5 was "too far/wide/fast", respectively. Other three questions were used to rate the perceived stress caused by each parameter of robot on a 5 points Likert scale.

## 6.5 Results and Discussion

In this section, we present the results for each part of the experiment.

### Training the robot

The values for each parameter, obtained at the end of the training of the robot are shown in Fig. 6.4, and in Table 6.5, where the values in parenthesis are the values that the robot can perform, and that are the actual values that were used in the second part of the experiment. The model predicts that extroverted female participants will prefer a closer distance than the other groups of participants, also that female participants will prefer gestures with

TABLE 6.3: Answers of participants in the Training phase - Questions 7-10, Likert Scale: 1 (not at all appropriate) to 5 (very appropriate)

|                  | 1       | 2      | 3      | 4      | 5      |
|------------------|---------|--------|--------|--------|--------|
| Chosen Distance  | 6.25 %  | 12.5 % | 0.00 % | 75.0 % | 6.25 % |
| Chosen Amplitude | 0.00 %  | 0.00 % | 31.3 % | 50.0 % | 18.7 % |
| Chosen Speed     | 0.00 %  | 18.7 % | 25.0 % | 43.8 % | 12.5 % |
| Final Behavior   | 06.25 % | 0.00 % | 56.2 % | 37.5 % | 0.00 % |

TABLE 6.4: Parameters for the introvert and the extrovert robot's behavior

|             | Distance (m) | Amplitude (%) | Speed (%) |
|-------------|--------------|---------------|-----------|
| Extro Robot | 1.20         | 100.0         | 100.0     |
| Intro Robot | 0.40         | 20.0          | 40.0      |

higher amplitude than male participants with the same personality as theirs (extroversion/introversion) and that extroverted male participants will prefer a faster speed for the gestures than the other groups of participants. As our model is based on a weighted mean of the activation values of each parameter in the EM, we applied a weighted t-test using the software R for a statistical analysis on the differences of the predicted parameters. The only significant difference was found in the preferred amplitude between the extrovert female group (0.83 m) and the introvert male group (0.44 m) with  $t = 2.327$ ,  $df = 7.905$ ,  $p = 0.048$ , and  $Std.err = 0.167$ .

### Testing the model

We compared our model against two different behaviors of the robot based on the introversion and extroversion personality traits. The means of the answers of the participants for each behavior on a 5 points Likert scale are shown in Table 6.6. We obtained different results for each personality-gender group. For each parameter (distance/speed/gesture) defining the behavior of the robot a two-way ANOVA was performed to identify main effects or interaction effects between the parameters and the personality and gender of the participants. We did not find any significant effect. A possible cause of this is the small number of participants that took part in the experiment. For this reason, we divided the data by personality/gender and analyzed it separately with a pairwise t-test for each group.

TABLE 6.5: Predicted parameters of the robot's behavior by personality and gender

|              | Distance (m) | Amplitude (%) | Speed (%)    |
|--------------|--------------|---------------|--------------|
| Extro Female | 0.69 (0.60)  | 83.0 (80.0)   | 86.0 (80.0)  |
| Extro Male   | 0.73 (0.80)  | 66.0 (60.0)   | 93.0 (100.0) |
| Intro Female | 0.82 (0.80)  | 63.0 (60.0)   | 74.0 (80.0)  |
| Intro Male   | 0.87 (0.80)  | 44.0 (40.0)   | 70.0 (60.0)  |

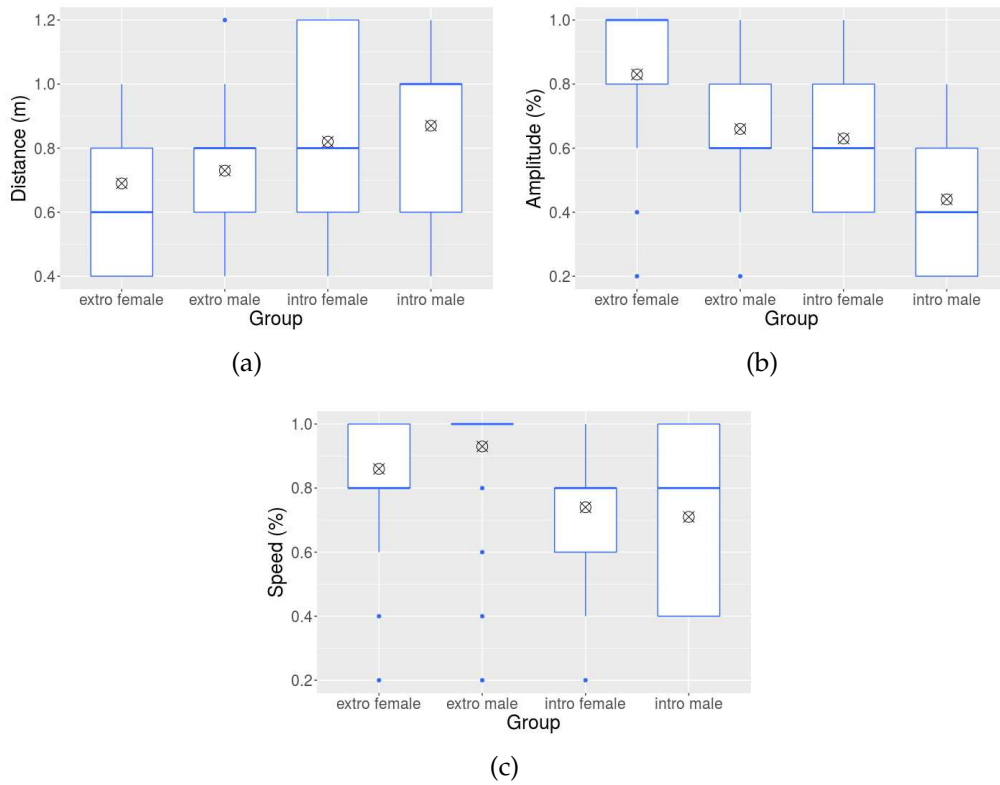


FIGURE 6.4: Predicted parameters of gesture by Personality/Gender. a) distance b) Amplitud c) Speed.

### Extrovert-Male

The distance of the proposed model was perceived as "more appropriate" than the distance of the extroverted robot behavior ( $p = 0.0087$ ). The amplitude of the introverted behavior was perceived as "more appropriate" than the amplitude of the extroverted behavior ( $p = 0.02$ ). In Table 6.6, Extro M section shows the means of each parameter of the different behaviors of the robot. The model has a mean closer to 3 ("appropriate") than the introverted and extroverted behaviors in the parameters of distance and amplitude. This can also be seen in Figs. 6.5(b) and 6.5(c). The speed of the extroverted robot was chosen as "appropriate" more times than the other behaviors (see Fig. 6.5(a)).

### Introvert-Male

The distance of the introverted robot behavior was perceived as "less appropriate" than the distance of the proposed model ( $p = 0.0022$ ), and as "more appropriate" than the extroverted robot behavior (0.0014). In Table 6.6, Intro M section shows the means of each parameter of the different behaviors of the robot. The model has a mean closer to 3 ("appropriate") than the introverted and extroverted behaviors in the parameters of distance and speed.

TABLE 6.6: Comparison of users' preferences of the generated model and the introvert and the extrovert robot's behaviors. Means and Variance of the 5 points Likert scale questionnaire.

|           |                    |                    |                    |
|-----------|--------------------|--------------------|--------------------|
| Extro M   | Model              | Intro R            | Extro R            |
| Speed     | 3.55 (0.77)        | 2.66 (2.25)        | <b>3.22 (0.19)</b> |
| Amplitude | <b>3.22 (0.19)</b> | 2.66 (1.25)        | 3.55 (0.27)        |
| Distance  | <b>2.77 (0.44)</b> | 3.33 (0.50)        | 1.88 (0.36)        |
| Intro M   | Model              | Intro R            | Extro R            |
| Speed     | <b>2.87 (0.69)</b> | 2.75 (0.50)        | 3.25 (0.50)        |
| Amplitude | 2.75 (0.78)        | <b>3.00 (0.85)</b> | 3.50 (0.57)        |
| Distance  | <b>3.00 (0.28)</b> | 3.37 (0.83)        | 1.87 (0.12)        |
| Extro F   | Model              | Intro R            | Extro R            |
| Speed     | <b>3.00 (0.5)</b>  | 2.40 (0.8)         | 3.80 (0.2)         |
| Amplitude | <b>3.60 (0.30)</b> | 3.00 (1.00)        | 2.80 (1.20)        |
| Distance  | 2.60 (1.30)        | <b>3.37 (0.83)</b> | 1.80 (0.20)        |
| Intro F   | Model              | Intro R            | Extro R            |
| Speed     | 2.50 (0.33)        | 2.50 (0.33)        | 3.25 (0.25)        |
| Amplitude | <b>3.25 (0.25)</b> | 2.75 (0.91)        | 3.50 (0.33)        |
| Distance  | 3.25 (0.25)        | 3.75 (0.25)        | 2.75 (0.25)        |

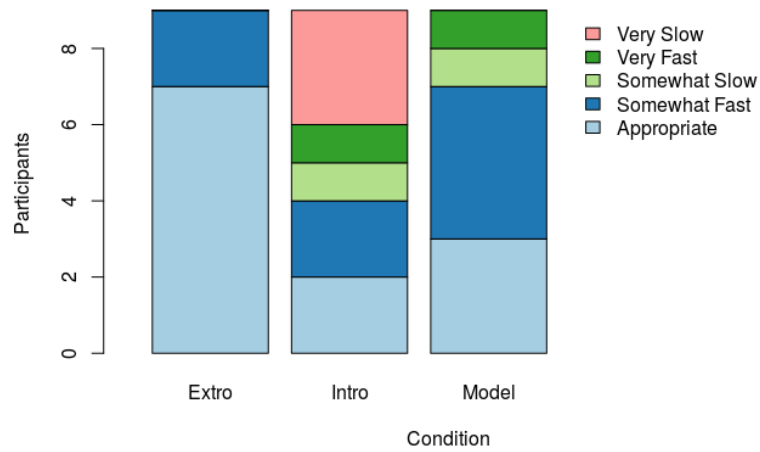
### Extrovert-Female

The distance of the introverted robot behavior was perceived as "more appropriate" than the distance of the proposed model ( $p = 0.0269$ ), and than the extroverted robot behavior (0.0012). The distance of the introverted behavior was perceived different as "somewhat far", while the extroverted behavior was perceived as "somewhat close / very close" ( $p = 0.0087$ ). In Table 6.6, Extro F section shows the means of each parameter of the different behaviors of the robot, the model has a mean closer to 3 ("appropriate") than the introverted and extroverted behaviors in the parameter of speed.

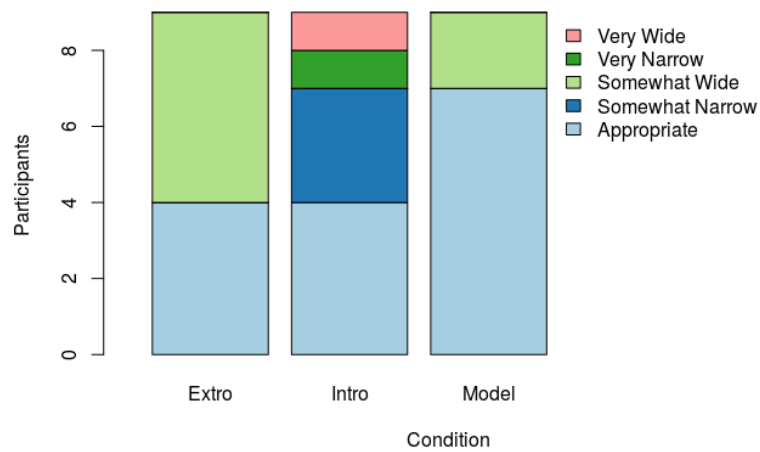
### Introvert-Female

There were no significant differences on the parameters of the different robot behaviors. In Table 6.6, Intro F section shows the means of each parameter of the different behaviors of the robot.

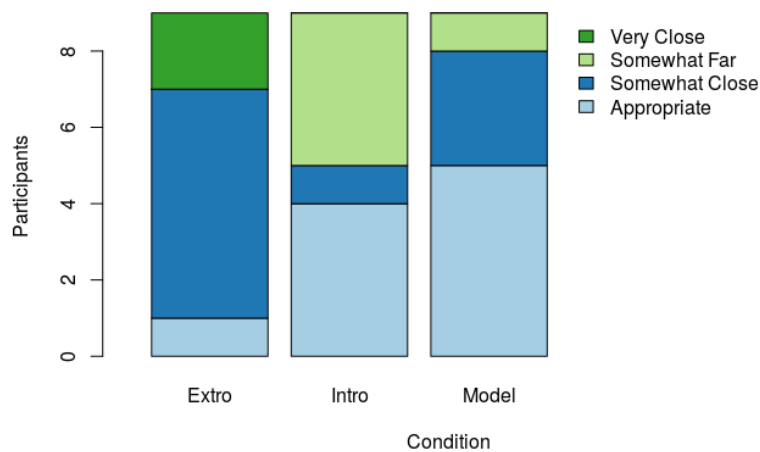
The behavior of the robot generated by the proposed model got an advantage over the introverted behavior and the extroverted behavior in some parameters in most of the personality/gender groups. Even when the differences were not significantly different, we can see a better performance of it. A larger group of participants would be needed so as to verify the differences. The parameter of distance of the proposed model was rated as "appropriate" more than the distance of the other behaviors with a difference that showed



(a) Speed



(b) Amplitude



(c) Distance

FIGURE 6.5: Parameter preferences of the Extrovert-Male participants in the different robot behaviors. Extro: Extroverted robot, Intro: Introverted robot, Model: Proposed Model. a) Speed b) Amplitude c) Distance



to be statistically significant as stated above. The accuracy of the model can be improved by training with more users. Also, for the sake of simplicity, the robot's behavior was restricted to 5 values for each parameter. Otherwise, the model could have been better rated by the participants in the testing phase. We can see that introverted male participants rated with a mean of 2.87 the speed of the robot's gesture generated with the model (see Table 6.6), meaning something slower than an appropriate value, the used value was 60%, but the value given by the model was 70%, which was a higher speed. Similar to this, the extroverted participants rated the speed of the robot's gesture generated with the model as faster than an appropriate value (mean 3.55), the used value was 100%, but the value given by the model was 93%, which was a slower speed. This shows that personality and gender can be used to predict user's preferences of robot's behaviors. Our hypothesis, that the robot's behavior generated with the interaction of individuals of different personalities and gender will best match with preferences of new users, was partially confirmed, as our model did not fit all the parameters of the different groups. Nevertheless, we are convinced that if we train our model with more individuals it can give better results.

## 6.6 Contributions and Conclusion

In this chapter, we presented our framework based on an Episodic-Like Memory and a cognitive model of emotions (OCC) and the use of this framework to create a robot model behavior based on the personality and gender of its users. We trained the model with 16 participants, 4 participants for each group of personality/gender, and tested it with other 26 participants. Results are promising as per the discussions above.

One contribution of this work is the combination of the OCC model with the Episodic-Like Memory. Because the OCC model does not specify how to use the memory on generating the emotions, we designed a mechanism to use the events on memory to generate the emotion of "Hope", which at the same time is used to ponder memory events on the Episodic-Like Memory.

Another contribution of this chapter is the evidence, showed in the results of the presented experiment, that an adaptive model based on personality and gender for robot behaviors could give better results than a predefined robot behavior, even if this behavior is based on theories like the Similarity Attraction Theory or the Complementary Needs Theory.

The use of personality traits to create our model, performed well to predict user preferences, which is one of the objectives of this thesis. Nevertheless, our other objective is to increase motivation and performance of people when they are performing a task. The experiments presented so far about users personality did not give us any cues on how to increase motivation and performance on the participants, even if we can perceive differences among personalities, we were not able to increase the performance of the users through the use of the Big 5 Personality Model. For this reason, we opted to use other theory to model the personality, which is more linked with performance, this theory is called the Regulatory Focus Theory, presented in Chapter 2.

The work done on this chapter, was presented in the International Conference on Robot and Human Interactive Communication (RO-MAN), Lisbon, Portugal, 2017,

In the next chapter, we will present an HRI experiment based on the Regulatory Focus Theory, which gives results showing an increased performance of the participants according to the theory.



## Chapter 7

# Analysis of Relation Between User Performance and the Regulatory Focus Theory

In the previous chapter, we presented our framework and how it can be used to learn user preferences based on personality and gender. Nevertheless, the use of the Big 5 personality model did not give us any cues on how to improve user's performance during a task.

More and more research works in which robots are part of social human centered environments are developed. The role of the robot in these environments can for example be a personal companion (Breazeal, 2017), health care assistant for children with autism (Chevalier et al., 2017) and elderly people (Hamada et al., 2016), or a teacher for children (Tazhigaliyeva et al., 2016).

The simple presence of a robot can induce both positive and negative effects on people. One example of negative effect is represented by the Social Facilitation effect (Zajonc et al., 1965). According to this effect, the mere presence of a robot can have a negative impact on the performance of an user in a difficult task (Cruz-Maya, Ferland, and Tapus, 2015).

Studies have been done in the field of social robotics with the purpose of using the motivation of the user in order to improve his/her performance and this was mainly tested in activities related to physical exercises. Fasola and Mataric (Fasola and Mataric, 2013) have done such a study for elderly people. In (Süssenbach et al., 2014), the authors used the robot as a fitness companion. Other studies include the usage of robot's gaze to increase user's motivation (Andrist, Mutlu, and Tapus, 2015), and the use of anthropomorphic robot expressions using robot eyes and arms to maintain learning motivation in elderly people (Osawa et al., 2010).

In this chapter, we explore the usage of another psychology theory, called Regulatory Focus Theory, in order increase users performance on their task.

## 7.1 Using Regulatory Focus Theory to improve User Performance

In this chapter, we propose the use of motivation based on the Regulatory Focus theory (Crowe and Higgins, 1997), introduced in Chapter 2, in order to match the Chronic Regulatory State of the participants with a Regulatory oriented strategy used by a robot. The Regulatory Focus theory states that people have one of the two different inclinations for decision making: promotion focus or prevention focus. According to this theory, promotion focus is related to risk situations, while prevention focus is related to security. Chronic Promotion Focus people are more inspired by positive models, which emphasize strategies for achieving success. Chronic Prevention Focus people are more inspired by negative models, which highlight strategies for avoiding failure (Lockwood, Jordan, and Kunda, 2002). In this way, Promotion people will focus on obtaining more gains, and Prevention people will focus on not having losses. Furthermore, it was demonstrated that these states can be induced, naming these states as Induced Promotion Focus and Induced Prevention Focus. Mismatch of the induced regulatory state with the Chronic Regulatory State can be counterproductive, resulting in a lower performance of a person in a task, and also an increase of that person's stress level.

To the best of our knowledge, regulatory focus has not been studied before in the field of social robotics. It has been studied in the field of virtual agents (Faur, Martin, and Clavel, 2015), where different strategies were used by a virtual agent in a gaming scenario. Results show a regulatory fit effect on the likability of the game for prevention focus users.

In this chapter, we investigate the effect of regulatory focus induced by a robot to a group of participants, testing the match and mismatch of Chronic Regulatory State of the participants and the Regulatory oriented strategy used by a robot, when the participants performed a Stroop test.

### 7.1.1 Hypotheses

Based on the Regulatory Focus Theory, we elaborated the following hypotheses:

- H1. When the robot uses a Promotion oriented strategy to motivate the participants, the participants with a Chronic Promotion Focus, should perform better than participants with a Chronic Prevention Focus.

- H2. When the robot uses a Prevention oriented strategy to motivate the participants, the participants with a Chronic Prevention Focus, should perform better than participants with a Chronic Promotion Focus.
- H3. When the robot uses an oriented Strategy not Matching the Chronic Regulatory Focus of the participants, they will be more stressed than participants to which the robot uses a Matching oriented Strategy.

## 7.2 Case Study: Stroop Test with Robot Instructions Based on the Regulatory Focus Theory

In this chapter, we designed an experiment using a non-verbal word color Stroop test (Stroop, 1935). We developed two types of items (congruent and incongruent) and presented them to the participants in a random order. The purpose of the task was to increase the cognitive load of the participants. The test was displayed on a computer monitor. Before starting the test, the participants were instructed on how to perform the task (using a computer mouse to press on the button, which corresponds to the color of the text). Furthermore, they had 60 trials to practice the test. For the experiment, the participants had to complete 50 trials. After finishing the practice test, the participants had to fill the Mood Questionnaire developed by Crowe and Higgins (Crowe and Higgins, 1997).

Participants were told to pay attention to the instructions given by the robot. They were instructed to start the task when the robot told them that they could start. In order to induce the Regulatory focus state in the participants, we developed 3 sets of instructions to be spoken by the robot. Therefore, we had 3 conditions, which are presented in the following section. After finishing the task, the participants were asked again to fill in the Mood Questionnaire and the Godspeed Questionnaire (Bartneck et al., 2009) (the sections for Likability, Perceived Intelligence, and Perceived Safety). When the experiment was finished, all the participants received some chocolate to show our appreciation for their help.

TABLE 7.1: Number of participants by condition and group. C.Pro = "Chronic Promotion State", C.Pre = "Chronic Prevention State".

| Control |         | Induced Promotion |         | Induced Prevention |         |
|---------|---------|-------------------|---------|--------------------|---------|
| Group A | Group B | Group C           | Group D | Group E            | Group F |
| C. Pro  | C. Pre  | C. Pro            | C. Pre  | C. Pro             | C. Pre  |
| 7       | 4       | 7                 | 4       | 7                  | 4       |

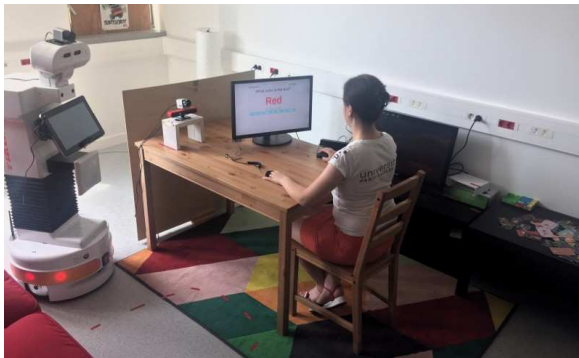
## 7.3 Methods

### 7.3.1 Conditions

Thirty three participants agreed to take part in this experiment. We developed a between subjects design and we assigned participants of both Chronic regulatory states to each condition. The distribution of the participants in each of our 6 groups can be seen in Table 7.1 (C. Pro stands for Chronic Promotion State, while C. Pre stands for Chronic Prevention State).

We used 3 conditions to test our hypotheses: Control condition, Promotion Robot strategy, and Prevention Robot strategy. The robot used was the TIAGo robot from PAL Robotics, that consists of a mobile base, a torso lift, and a head. It has a height of 110 to 145 cm, a weight of 70 kg, and 5 DoF (without arms). The instructions given by the robot in each condition were different but all of them prompted the participants to answer as fast as possible without making any mistakes. The robot was located at a distance of 1.2 m. - 1.5 m.

The instructions given by the robot in each condition are:



(a) Scenario



(b) Table with cards

FIGURE 7.1: (a) Scenario used in the experiment; (b) Table with cards used as a negative motivation.

**Control:** “Please complete the Stroop test on the computer. You have to answer as soon as possible, your score will be measured with respect to the number of correct answers, and the time spent for each test. I will say it again. You have to answer as soon as possible, your score will be measured with respect to the number of correct answers, and the time spent for each test. You can start now”.

**Promotion Robot:** The same speech of the Control condition, adding the following phrase before saying “You can start now”: “If your score is better than seventy percent of the participants you will get a special reward, otherwise you will have to arrange the cards on the black table behind you by descending order”.

**Prevention Robot:** The same speech of the Control condition, adding the following phrase before saying “You can start now”: “As long as you are not part of the seventy percent of the participants with lower score, you will not have to arrange the cards on the black table behind you by descending order, but you will get a special reward”.

### 7.3.2 Regulatory Focus Questionnaire - Proverb Form

The Chronic regulatory state of the participants was obtained by applying the Regulatory Focus Questionnaire - Proverb Form (RFQ-PF 18 items), originally developed in French (Faur, Martin, and Clavel, 2017). We translated the proverbs, by finding their English equivalents.

This questionnaire was chosen as it does not depend only on the personal history of the person, as is the Regulatory Focus Questionnaire (Higgins et al., 2001). Furthermore, it is not related to academic questions like the General Regulatory Focus Measure (Lockwood, Jordan, and Kunda, 2002). Instead, the usage of proverbs allows the evaluation of the strategy regulation preferences in a discrete and subtle way.

### 7.3.3 Measures

In order to validate our hypotheses, we used the Reaction Time expended for the participants to complete each trial of the Stroop Test, and the number of errors made. We compared the participant groups in the different conditions using the total reaction time, the reaction time for congruent trials (corresponding word with color), and the reaction time for incongruent trials (not corresponding word with color). The same was done for the number



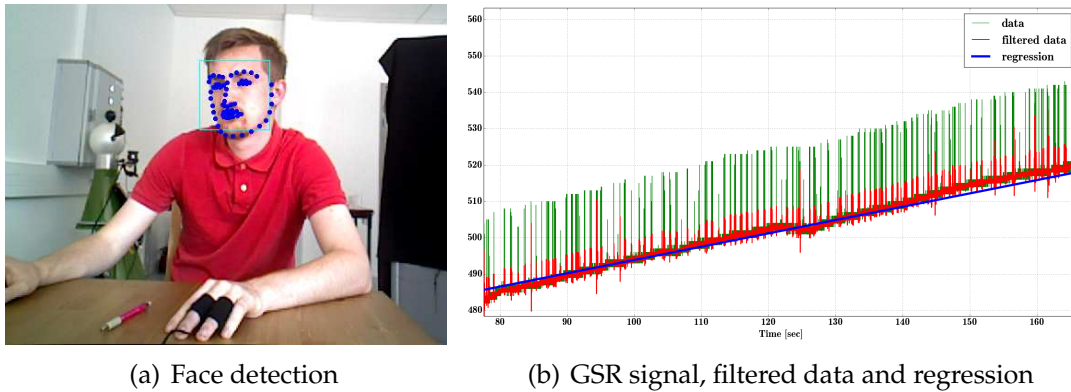


FIGURE 7.2: (a) Face and face features extraction of the participants, (b) GSR signal filtered data and regression showing an increase of stress on the participant

of errors, total errors, errors for congruent trials, and errors for incongruent trials.

We also measured the heart rate, the respiration rate, the blinking rate, and the skin conductance of the participants, with the purpose of detecting stress and anxiety.

The heart rate, respiration rate, and blinking were extracted using an Asus Xtion RGB camera. The faces and facial features were detected using the Dlib toolkit (King, 2009) (see Figure 7.2(a)). For blinking, we used the method presented in (Agrigoroaie and Tapus, 2017). The skin conductance was measured using the Grove - GSR Sensor<sup>1</sup>. All the physiological measures were compared using a linear regression on the filtered data (with exception of blinking, which was measured using the total number of blinks detected), using the difference between the beginning and the end of the regression of the signal, an example of this (GSR signal with zoom) is presented in Figure 7.2(b)).

## 7.4 Results and Discussion

We found statistical differences in the time and errors of the participants on the Stroop Test in the different conditions of the experiment, as well as correlations between the physiological measures and the Chronic and Induced Regulatory state of the participants. The mean and standard deviation of the Time and Errors of the participants on the Stroop Test, divided by groups (see Table 7.1), are presented in Tables 7.2, and 7.3, respectively.

<sup>1</sup>[http://wiki.seeed.cc/Grove-GSR\\_Sensor/](http://wiki.seeed.cc/Grove-GSR_Sensor/)

TABLE 7.2: Mean and Std Deviation of the time (secs) of the participants

| Group | Total Time     | Congruent-color Time | Incongruent-color Time |
|-------|----------------|----------------------|------------------------|
|       | Mean - Std Dev | Mean - Std Dev       | Mean - Std Dev         |
| A     | 59.00 - 11.56  | 25.58 - 05.30        | 33.41 - 06.64          |
| B     | 57.14 - 03.21  | 25.02 - 02.39        | 32.12 - 01.49          |
| C     | 52.34 - 08.19  | 23.86 - 04.03        | 28.48 - 04.39          |
| D     | 56.72 - 10.96  | 23.77 - 04.59        | 32.95 - 06.43          |
| E     | 56.51 - 06.09  | 25.16 - 02.57        | 31.45 - 04.33          |
| F     | 46.50 - 06.36  | 21.45 - 03.50        | 25.05 - 02.91          |

TABLE 7.3: Mean and Std Deviation of the number of errors of the participants

| Group | Total Errors   | Congruent-color Errors | Incongruent-color Errors |
|-------|----------------|------------------------|--------------------------|
|       | Mean - Std Dev | Mean - Std Dev         | Mean - Std Dev           |
| A     | 0.42 - 0.78    | 0.14 - 0.37            | 0.28 - 0.48              |
| B     | 0.25 - 0.50    | 0.25 - 0.50            | 0.00 - 0.00              |
| C     | 0.16 - 0.40    | 0.00 - 0.00            | 0.16 - 0.40              |
| D     | 0.25 - 0.50    | 0.00 - 0.00            | 0.25 - 0.50              |
| E     | 0.71 - 0.48    | 0.14 - 0.37            | 0.57 - 0.53              |
| F     | 0.00 - 0.00    | 0.00 - 0.00            | 0.00 - 0.00              |

We analyzed the Time and Errors as dependent variables, we applied a one-way ANOVA using the different groups of the experiment as factors (independent variables). We did not find any statistical difference among the groups. As this could be due to the small size of the groups, we proceeded to analyze each pair of groups with t-tests separately. No differences or correlations were found in relation with the mood of the participants and the different groups. The same result was obtained in the case of the Godspeed Questionnaire.

### Hypothesis 1

We did not find evidence that participants with Chronic Promotion State (Group C) performed better than participants with Chronic Prevention State (Group D), when the robot used a Promotion oriented strategy. Nevertheless, we found that participants with Chronic Promotion State performed better

TABLE 7.4: Tests to validate the hypothesis 1

| Total errors - T-Test   |             |         |         |        |
|---|-------------|---------|---------|--------|
| Group C   | Group E     | P-value | t       | df     |
| 0.16  | 0.71        | 0.0381  | 2.9835  | 12     |
| Promotion strategy and Chronic Promotion State - Pearson Test |             |         |         |        |
| Group C   | Correlation | P-value | t       | df     |
| C   | -0.8629     | 0.0269  | -3.4152 | 4.0000 |

(having less errors in the Stroop Test) when the robot used a Promotion oriented strategy (Group C) than when it used a Prevention oriented strategy (Group E). This difference was found in the total errors in the Stroop Test. Also, we found a negative correlation between Time and Chronic Promotion State of the participants when the robot used a Promotion oriented strategy (Group C), meaning that a higher Promotion state was related with a lower time. The result of the t-test and the Pearson correlation test are presented in Table 7.4.

### Hypothesis 2

We found that participants with Chronic Prevention State (Group F) performed better in time and number of errors than participants with Chronic Promotion State (Group E), when the robot used a Prevention oriented strategy. This difference was present in the overall time, in the incongruent color trials time, and in the errors in the incongruent color trials. Moreover, they performed better than participants in the control condition (Group B). The results of the t-tests are presented in Table 7.5.

### Hypothesis 3

We found evidence supporting the relation of Stress with a mismatch of the Strategy used by the robot and the Chronic Regulatory State of the participants. Analyzing the heart rate (HR) with an one-way ANOVA, we found differences in the groups. Moreover, by applying a pairwise t-test comparison, we found that participants with Chronic Prevention State had higher heart rates when the robot used a Promotion oriented strategy (Group D) than when the robot used a Prevention oriented strategy (Group F) or no strategy (Group D), giving us cues that participants in such conditions were more stressed.

TABLE 7.5: T-Tests to validate the Hypothesis 2

| Total time (secs)                    |              |         |        |        |
|--------------------------------------|--------------|---------|--------|--------|
| Group - Mean                         | Group - Mean | P-value | t      | df     |
| B 57.14                              | F 46.50      | 0.0355  | 2.9835 | 4.4416 |
| E 56.51                              | F 46.50      | 0.0428  | 2.5480 | 6.1288 |
| Incongruent-color trials time (secs) |              |         |        |        |
| Group - Mean                         | Group - Mean | P-value | t      | df     |
| B 32.12                              | F 25.05      | 0.0096  | 4.3197 | 4.4828 |
| E 31.45                              | F 25.05      | 0.0178  | 2.9226 | 8.5510 |
| Incongruent-color trials errors      |              |         |        |        |
| Group E                              | Group F      | P-value | t      | df     |
| 0.57                                 | 0.00         | 0.0300  | 2.8284 | 6.0000 |

TABLE 7.6: Tests to validate the hypothesis 3

| Heart rate and Groups - One-way Anova              |              |         |         |    |
|--|--------------|---------|---------|----|
| P  |              | F-value | df      |    |
| 0.0368   |              | 2.8328  | 5       |    |
| Heart Rate and Groups - Pairwise T-test comparison |              |         |         |    |
| Group - Mean                                       | Group - Mean | P-value |         |    |
| B -0.41  | D 6.01       | 0.0221  |         |    |
| D 6.01   | F -3.21      | 0.0018  |         |    |
| Time and Respiration rate - Pearson Test           |              |         |         |    |
| Group  | Correlation  | P-value | t       | df |
| E  | 0.9336       | 0.0020  | 5.8296  | 5  |
| Time and Blinking rate - Pearson Test              |              |         |         |    |
| Group  | Correlation  | P-value | t       | df |
| D  | -0.9996      | 0.0165  | -38.513 | 1  |
| E  | -0.9300      | 0.0023  | -5.6607 | 5  |
| GSR and Prevention Score - Pearson Test            |              |         |         |    |
| Group  | Correlation  | P-value | t       | df |
| C  | 0.89013      | 0.0429  | 3.3832  | 3  |

We also found correlations between Time and respiration rate, and Time and blinking of the participants. When the robot used a Prevention oriented strategy, the Total Time spent in the Stroop test by the participants with Chronic Promotion State (Group E) presented a positive correlation with the respiration rate. Blinking presented a negative correlation with the time when the robot used a not matching strategy in both Chronic Prevention (Group D) and Promotion (Group E) States. We can interpret this as a greater visual fatigue, when the participants tried to focus on the task, when

the robot uses a mismatched strategy.

Analyzing the score of the Chronic regulatory state of the participants in relation with the respiration rate, we found correlations between them. A higher Chronic Promotion State was related with a higher respiration rate when the robot used a Prevention oriented strategy (Group D). In the same way a positive correlation was found between the respiration rate and the Chronic Prevention State when the robot used a Prevention oriented strategy or no strategy. This could imply that a Prevention strategy increases the cognitive load (cognitive load may lead to overbreathing (Grassmann et al., 2016)) for both kind of Chronic Regulatory states, or at least that this strategy does not help to decrease the cognitive load on the participants.

Regarding the data provided by the GSR Sensor, only a negative correlation has been found between the score of Prevention Regulatory State and the Skin Conductance in the participants with Chronic Promotion State when the robot used a strategy matching their chronic regulatory state (Group C). However, this can hardly be found as evidence of stress, since the correlation is not with the Chronic Regulatory state of the participants.

The results of all the tests to validate Hypothesis 3 are shown in Table 7.6.

## 7.5 Contributions and Conclusion

The main contribution of this chapter is that Regulatory Focus Theory can be used in Human-Robot Interaction to improve users performance.

In this chapter, we presented an experiment where a robot gave instructions to complete a Stroop Test to a group of participants. The participants were divided in groups with respect to their score on a test of Regulatory Focus. The robot had 3 conditions, in the first and control condition, the robot did not include any regulatory strategy. In the second condition the robot gave instructions that included a Promotion oriented strategy, while for the third condition it included a Prevention oriented strategy.

The results showed evidence that support most of our hypotheses. Only hypothesis H1 was not supported completely. Nevertheless, participants with Chronic Promotion State performed better in the condition of the robot with Promotion oriented strategy than in the condition with Prevention oriented strategy. Hypothesis H2 was supported as the participants with Chronic Prevention State performed better than participants with Chronic Promotion State when the robot had a Prevention oriented strategy. Hypothesis H3 was

supported by correlations between different physiological signals and performance in Time of the participants, meaning that an increase in stress and cognitive load is correlated with a mismatch of the Regulatory Strategy of the robot and the Chronic Regulatory state of the participants.

The work done on this chapter, was presented in the International Conference on Social Robotics (ICSR), Tokyo, Japan, 2017,

In the next chapter, we will continue exploring the Regulatory Focus Theory, using gestures and varying the speed of the speech instead of changing the content of it, in order to minimize the user stress and increase user performance.



## Chapter 8

# Evaluating Different Robot Behaviors Based on the Regulatory Focus Theory

In the previous chapter, we presented the evidence of how the Regulatory Focus Theory can be used in Human-Robot Interaction to improve users' performance by the use of speech instructions before of the task.

In the field of Human-Robot Interaction (HRI), some research works have been done, with the purpose of finding a good manner on how robots should give advice to their users. In (Strait, Canning, and Scheutz, 2014), the authors analyzed robot advice and strategies based on human-human interactions. Furthermore, the authors in (Torrey, Fussell, and Kiesler, 2013) made use of hedges (to soften what was said) and discourse markers, such as "kind of" and "basically". It was found that when the robot used these features, it seemed more considerate, likable, and less controlling. Another study designed for motivating the elderly during physical exercises with a coach robot, found evidence that support the use of relational discourse in increasing intrinsic motivation (Fasola and Mataric, 2012). A study in Human-Robot Negotiation using a telepresence robot, proposes the use of handshaking before the negotiating phase, which resulted in increased cooperation between negotiators (Bevan and Stanton Fraser, 2015). Moreover, in the context of negotiation between humans and robots, guilt and agency have been investigated, but the results suggest that these factors have no influence on the overall concession in the negotiation task (Stoll, Edwards, and Edwards, 2016).

In this chapter, we propose the use of different robot behaviors, based on the Regulatory Focus Theory, to increase user's performance, using gestures and varying the speed of the speech instead of changing the content of it, in order to minimize the user's stress and increase user's performance.



## 8.1 Regulatory Focus Theory

### 8.1.1 Regulatory Focus and Regulatory Fit

Regulatory Focus, introduced in Chapter 2, is a theory from social psychology proposed by Crowe and Higgins (Crowe and Higgins, 1997). The Regulatory Focus theory proposes the existence of two types of self regulatory states that influence the motivation to perform a task. These states are: Chronic Promotion Focus and Chronic Prevention Focus. Individuals with a higher level of Promotion Focus are more likely to take risks in order to maximize their gains and individuals with higher level of Prevention Focus are more cautious when taking decisions and they focus on not having losses.

Higgins (Higgins, 2005) also proposes Regulatory Fit, a theory linked to the Regulatory Focus, which can be viewed as follows: if an individual receives a message with the same frame as their own regulatory state (promotion or prevention), they are more likely to do what the message says, by increasing the motivational orientation of the person. In (Cesario, Higgins, and Scholer, 2008), the authors discuss the use of Regulatory Fit so as to increase the effectiveness of changing attitudes and behavior.

An increase of persuasiveness, according to Higgins, can be achieved by non-verbal cues such as body gestures and the speed of the speech. Making a lot of movements, leaning forward, and speaking faster, are more persuasive cues for individuals with Chronic Promotion State. Instead, making precision gestures and speaking more slowly, are more persuasive cues for individuals with Chronic Prevention State (Cesario and Higgins, 2008).

### 8.1.2 Regulatory Fit and Negotiation in HRI

As stated by Higgins in (Higgins, 2005), fit has significant implications for improving the quality of life in interpersonal conflicts and the negotiation process needs to be fair and equitable. In human-robot interaction (HRI), if the robot expresses a behavior matching the regulatory focus state of the users, the users could increase their satisfaction with the negotiation and commitment to the agreement, which could imply less stress on them.

To the best of our knowledge, Regulatory Focus and Regulatory Fit have not been studied before in a negotiation scenario in HRI. Personal robots could use the behaviors from human-human interaction proposed in the field of social psychology, with the purpose to be more persuasive on their roles



FIGURE 8.1: Negotiation scenario with a Pepper Robot

in Human-Robot Interaction. A way of testing their persuasion style, a negotiation game could be used. Regulatory Focus in the context of negotiation has been studied in human-human interaction. In (Galinsky et al., 2005), the authors found that promotion focused negotiators achieved more advantageous distributive outcomes than did prevention focused negotiators. Other study (Appelt et al., 2009), shows that when negotiation focuses on price, buyers adopt a prevention focus strategy and sellers adopt a promotion strategy.

In this chapter, we present an analysis of three different robot behaviors: robot control condition, robot Promotion based behavior, and robot Prevention based behavior. The behavior of the robot was presented to the user in a negotiation scenario (see Fig. 9.1). Also, participants were divided in groups based on their Regulatory States: in Promotion and Prevention groups, respectively.

## 8.2 Case Study: Negotiating with a Robot with Behavior based on the Regulatory Focus Theory

### 8.2.1 Hypothesis

Based on the Regulatory Focus and Regulatory Fit theories, described in section 8.1.2, we propose the following hypotheses:

- H1) Participants with Chronic Promotion Focus, interacting with a robot in a Negotiation scenario, will give more concessions when the robot shows a Promotion based behavior, than when the robot shows a Prevention based behavior.
- H2) Participants with Chronic Prevention Focus, interacting with a robot in a Negotiation scenario, will give more concessions when the robot shows a Prevention based behavior, than when the robot shows a Promotion based behavior.
- H3) Participants matching their Chronic Regulatory Focus with the robot behavior, will be less stressed than the participants not matching their Chronic Regulatory Focus with the robot behavior.

### 8.2.2 Negotiation game Scenario

The negotiation game used in this work, was first proposed in the field of psychology in (De Dreu and Van Lange, 1995), and modified and used in HRI by (Stoll, Edwards, and Edwards, 2016). In this game, participants were instructed to play the role of a seller, selling a mobile phone to a robot. The negotiation included three features to negotiate: price, warranty, and services. Also there were ten levels of these features, where the first level was the most convenient for the sellers, and the last level was the most convenient for the robot. Participants were told that each feature had associated an amount of points that they could gain as sellers if they succeeded selling the phone. The first level contained the highest price, the lowest warranty, and the lowest services, with 100 points associated to each feature. The last level contained the lowest price, the highest warranty, and the lowest services, with 10 points associated to each feature. This information was also posted on the wall behind the robot, so users could see it at any moment.

The game started with the robot (buyer) saying its offer in terms of the levels of the three features, then the participant (seller) accepted or refused

the offer. The interaction was done by using voice commands. In this step, the robot recognized the commands of "yes" and "no". If the user said "no", the robot asked for the level of each feature, here the robot recognized the commands of "level one", "level two", and so on until "level ten".

The robot (buyer) followed a predetermined pattern of offers, in order to present the same pattern to all the participants and avoid inconsistencies on the offers. The pattern followed by the robot was proposed in (De Dreu and Van Lange, 1995) in order to represent a cooperative-competitive strategy in the same pattern.

If the offer of the participant was better than the next offer in the pattern followed by the robot, then the robot accepted the offer of the participant and the negotiation finished. In the opposite case, the robot started a new round and this was repeated by a maximum of seven rounds. Participants were told that after some rounds, if they did not agree with the robot, it would say "good bye" and they could not sell the phone.

### 8.2.3 Robot Platform

The robot used in this work was the Pepper robot designed by Softbank robotics, which has the capabilities of face detection and tracking, voice recognition, and movement of the body and head to track the user. These capabilities are provided by the Naoqi framework. We disabled the tracking with the body of the robot and let working only the movement of the face. Also, we used the naoqi ROS driver to communicate the different modules used on the experiment.

### 8.2.4 Robot Speech

Each time the robot refused an offer, it took a random phrase from the list presented below:

- I consider that a better agreement should be (offer)
- Perhaps a better idea would be (offer)
- I am looking for a better package, I would like (offer).
- I'm afraid I could not agree to that, I propose (offer)
- I was hoping for something around (offer)
- I would not expect to pay more than (offer)

- I am afraid your offer does not go far enough, I propose (offer)

When the robot accepted the offer of the participant, it said "I think we have reached an agreement here". And in the case the robot finished the round seven, it said "We did not agree, I'm leaving, good bye".

To our understanding of the Regulatory Focus Theory, the used phrases do not represent any "promotion" or "prevention" strategy, since they are not stating the reward in the message.

### 8.2.5 Robot Speech Recognition

We used the module "ALSpeechRecognition" of the Naoqi Framework using the English language and the dictionary of the recognized words was the following: dictionary = ["yes", "no", "level one", "level two", "level three", "level four", "level five", "level six", "level seven", "level eight", "level nine"]. The speech recognition was paused each time the robot talked, in order to avoid self voice recognition of the robot. The recognized words were saved on memory using the module "ALMemory", subscribing to the event "WordRecognized". Each time the robot recognized a word, we compared to the words on the dictionary and if its associated probability valued surpassed a threshold of 30%, then the message was sent to the robot to execute the corresponding behavior.

### 8.2.6 Conditions

42 participants (37 men, 5 women) were recruited to take part in this experiment, 5 of them were discarded, 4 participants because of false speech recognition by the robot, finishing the experiment unexpectedly, and the other participant because of an important instruction missed by the experimenter.

There were 3 conditions: (1) the control condition, (2) the robot promotion based behavior condition, and (3) the robot prevention based behavior condition. The robot behaviors were designed accordingly to the theory of Regulatory Focus (Cesario and Higgins, 2008).

Participants of both Promotion and Prevention Regulatory Focus, were randomly assigned on each condition. In the control condition participated 7 promotion participants and 4 prevention participants. In the Promotion robot condition participated 6 promotion participants and 5 prevention participants. And finally, in the Prevention robot condition participated 10 promotion participants and 5 prevention participants.

### **Control Condition**

In the control condition, the robot only moved its head, tracking the face of the participants. The speed of its voice was the default speed.

### **Promotion Based Robot Behavior Condition**

In the Promotion Behavior condition, the robot beside moving its head, showed moving outward gestures, and it was leaning forward towards the participant. The speed of its voice was set to 115% of the default speed.

The postures of the Promotion based robot behavior are shown in Fig. 8.2. For each one of the two phrases, the robot chose randomly one posture.

The postures were designed using the Choregraphe Software and were run using the Module "ALAnimationPlayer". All of them started from the "Stand" posture of the module "ALRobotPosture".

The design of the movements of the robot was done using the Motion timeline of Choregraphe. An example of the angles and time used on this work is showed below, running from Timeline 1 to Timeline 3.

Timeline 1, Frame 18: [RElbow: 76,4 RElbowYaw: 74,4 RHand: 0,56 RShoulderPitch: 89,8 RShoulderRoll: -11,0 RWristYaw: 32,4 .

Timeline 2; Frame 12-40: [RElbow: 76,4 RElbowYaw: 74,4 RHand: 0,86 RShoulderPitch: 35,5 RShoulderRoll: -37,1 RWristYaw: 73,8 .

Timeline 3, Frame 18: [RElbow: 76,4 RElbowYaw: 74,4 RHand: 0,56 RShoulderPitch: 89,8 RShoulderRoll: -11,0 RWristYaw: 32,4 .

### **Prevention Based Robot Behavior Condition**

In the Prevention Behavior condition, the robot beside moving its head, showed pushing down gestures. The speed of its voice was set to 85% of the default speed.

The postures of the Prevention based robot behavior are shown in Fig. 8.3. For each one of two phrases, the robot showed randomly one posture.

## **8.2.7 Regulatory Focus Questionnaire - Proverb Form**

A Pre-experiment questionnaire was applied to the participants in order to obtain their Chronic Regulatory State. This questionnaire is called: Regulatory Focus Questionnaire - Proverb Form (RFQ-PF 18 items), originally developed in French (Faur, Martin, and Clavel, 2017). For our experiment, we

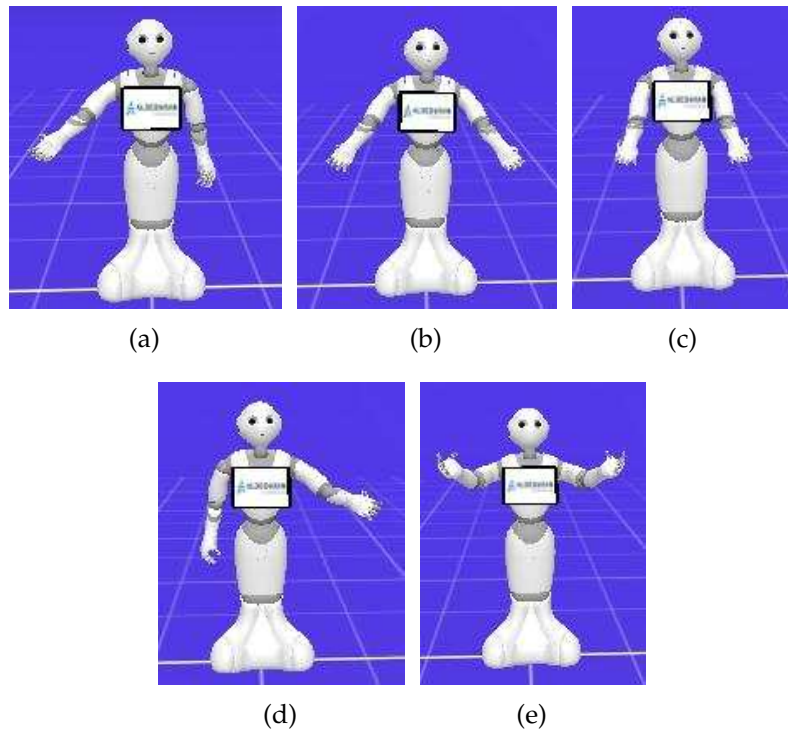


FIGURE 8.2: Postures of the Promotion based robot condition

used a translated version of the proverbs, using their English version. Only one proverb, for which we did not find an equivalent one, was substituted.

Unlike other questionnaires of Regulatory Focus, this one does not depend only on the personal history of the individual, like the Regulatory Focus

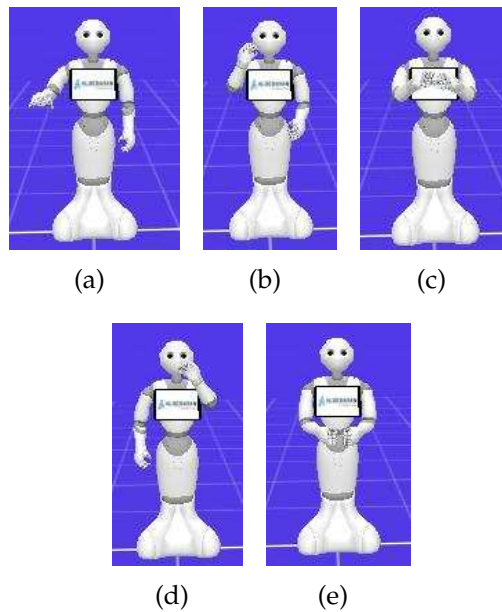


FIGURE 8.3: Postures of the Prevention based robot condition

TABLE 8.1: Mean and Std Deviation of the measures on the negotiation game

| Group | Sucess             | rounds      | init. offer        | final offer        | improv. offer      |
|-------|--------------------|-------------|--------------------|--------------------|--------------------|
|       | Mean - SD          | Mean - SD   | Mean - SD          | Mean - SD          | Mean - SD          |
| A     | 0.28 - 0.48        | 6.00 - 1.73 | 3.28 - 1.59        | 6.19 - 0.66        | 2.90 - 1.15        |
| B     | 0.25 - 0.50        | 6.25 - 1.50 | 3.83 - 1.13        | 5.83 - 0.88        | 1.50 - 0.79        |
| C     | <b>1.00 - 0.00</b> | 4.83 - 0.75 | 3.61 - 1.92        | <b>6.72 - 0.25</b> | 3.11 - 1.81        |
| D     | 0.40 - 0.54        | 5.80 - 1.30 | 3.53 - 1.67        | 5.66 - 1.45        | 2.13 - 1.21        |
| E     | 0.70 - 0.48        | 4.80 - 1.98 | 4.19 - 2.03        | 6.43 - 1.52        | 2.23 - 1.73        |
| F     | 0.20 - 0.44        | 6.20 - 1.78 | <b>1.73 - 1.64</b> | 5.93 - 0.98        | <b>4.20 - 2.03</b> |

Questionnaire (Higgins et al., 2001). Also, it is not related to academic questions such as the General Regulatory Focus Measure (Lockwood, Jordan, and Kunda, 2002). Instead, using proverbs allows to evaluate the chronic regulatory state in a discrete and subtle manner.

### 8.2.8 Measures

In order to validate our hypotheses, we used the average level of the offer of the participants, taking the initial offer, the final offer, and the difference between them (improvement of the offer), also the rounds taken on the negotiation, and the success or not in selling the phone, this last measure can be seen also as the success of the robot in buying the phone at a cheap price and/or advantageous warranty and service.

All the trials were taken into consideration, even the ones where there was no agreement, because we consider a measure of robot persuasiveness as successful if the robot "sell the phone".

Also, we measured some physiological signals: respiration rate, heart rate, blinking rate, and skin conductance of the participants. All of them were measured with the purpose to detect stress and anxiety on the participants.

Some of these measures were recorded using external sensors (the GSR sensor or the Thermal camera).

The respiration rate, heart rate, and blinking were recorded using an external Asus Xtion RGB-D camera.

We used the Asus Xtion RGB-D camera, instead of the one included on the Pepper robot, to facilitate the detection of the Faces for its post analysis.

The faces and facial features were detected using the Dlib toolkit (King, 2009) (see Fig. 8.4). We used the Grove - GSR Sensor to measure the skin





FIGURE 8.4: Negotiation scenario with a Pepper Robot

conductance <sup>1</sup>. The method used to extract the blinking rate is presented in (Agrigoroaie and Tapus, 2017). For comparison of the measures registered with the sensors, we used a linear regression on the filtered data, using the difference between the beginning and the end of the regression of the signal. The only exception was the blinking, which was measured using the total number of blinks detected.

Furthermore, the participants completed the Godspeed Questionnaire (Bartneck et al., 2009) (sections for Likability, Perceived Intelligence, and Perceived Safety).

### 8.3 Results and Discussion

We found statistical differences between the groups of participants when the robot behavior matched their Chronic Regulatory State and the groups of participants when it did not match. The results of the measures of the negotiation game are shown in Table 8.1.

The groups of participants and conditions are described below:

- Condition 1: Control Condition
- Condition 2: Robot Promotion Condition
- Condition 3: Robot Prevention Condition
- Group A: Condition 1 - Promotion Participants

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<sup>1</sup>[http://wiki.seeed.cc/Grove-GSR\\_Sensor/](http://wiki.seeed.cc/Grove-GSR_Sensor/)

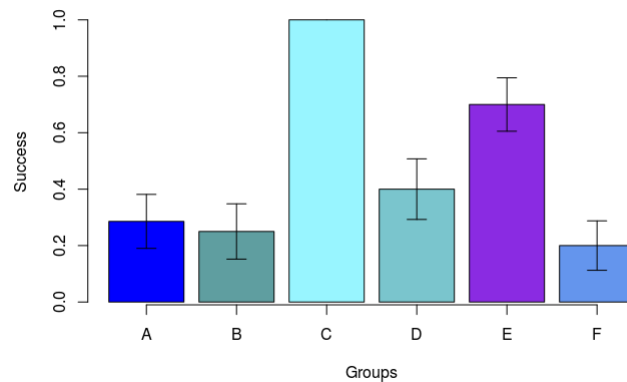


FIGURE 8.5: Robot success selling the phone by Group

- Group B: Condition 1 - Prevention Participants
- Group C: Condition 2 - Promotion Participants
- Group D: Condition 2 - Prevention Participants
- Group E: Condition 3 - Promotion Participants
- Group F: Condition 3 - Prevention Participants

We started our analysis with an one-way ANOVA, using the different groups of the experiment as factors. We did not found any statistical difference among the groups. As this could be due to the small size of the groups, we proceeded with pairwise comparisons between the groups and the factors of interest. In the following subsections, we discuss the results of the measures, linking them with each formulated hypothesis.

### 8.3.1 Hypothesis 1

Participants with Chronic Promotion Focus effectively gave more concessions to the robot when it presented a Promotion based behavior (Group C). It can be seen in Table 8.1, the scale goes from 0 to 1, where 1 means 100%, Group C was the only group where the robot achieved 100% of success on the negotiation. These results are shown in Fig. 8.5. The t-test between the Control Condition and the Promotion condition (Group A and Group C) shows a  $p = 0.007$ . Also, there are significant differences between groups B, D, and F with  $p$  values of 0.0148, 0.0353, and 0.0062, respectively.

TABLE 8.2: Mean and Std Deviation of the measures of the physiological signals of the different groups

| Group | Heart rate          | Resp. rate   | Blinking        | GSR            |
|-------|---------------------|--------------|-----------------|----------------|
|       | Mean - SD           | Mean - SD    | Mean - SD       | Mean - SD      |
| A     | -0.75 - 4.97        | 0.88 - 2.41  | 96.16 - 35.89   | -51.16 - 96.60 |
| B     | 4.38 - 9.40         | 1.26 - 0.58  | 98.33 - 57.70   | -29.54 - 19.79 |
| C     | -0.69 - 4.06        | 1.36 - 2.64  | 63.00 - 16.38   | -36.98 - 45.20 |
| D     | <b>5.19 - 9.72</b>  | 0.40 - 2.71  | 127.60 - 50.55  | -10.86 - 19.28 |
| E     | 0.23 - 9.48         | 1.41 - 2.66  | 94.87 - 64.60   | -13.66 - 38.24 |
| F     | <b>-5.23 - 6.02</b> | -0.37 - 2.36 | 152.00 - 143.75 | -19.23 - 47.05 |

Participants from Group C sold the phone to the robot, which was good for them, but also, they did at the expense of selling it at a good price for the robot (mean final offer of 6.72), they did the highest offer of all groups.

There is no significant difference on the rounds of the negotiation. Nevertheless, the Promotion people did less rounds than the Prevention people in all conditions. This can be due to the differences on the inner strategy of Promotion and Prevention people, where the tendency of Promotion people to take risks can lead them to make higher offers.

Moreover, we found evidence that support the Regulatory Focus and Regulatory Fit theories for Promotion Focus individuals, and that is possible to increase the persuasiveness of a robot in a negotiation game. This could be useful for personal robots, requiring such capabilities when negotiating with their users in everyday life.

### 8.3.2 Hypothesis 2

Participants with Chronic Prevention Focus did not give more concessions to the robot on the negotiation game when it presented a Prevention behavior (Group F).

It is possible that due to the strategy of prevention individuals, they did not make high offers to the robot, because they could had been trying to minimize their losses. This idea is reinforced by the results on the initial offer of the group (1.73), the lowest offer of all groups, significantly different than the group E (t-test  $p = 0.016$ ). The robot showing a Prevention behavior matched their own Prevention Focus, which could result in an increase on their motivation and strategy.

Moreover, this group increased their offer as no other group (see Table 8.1), it is shown in Fig. 8.6. The t-test analyzing this group against the groups

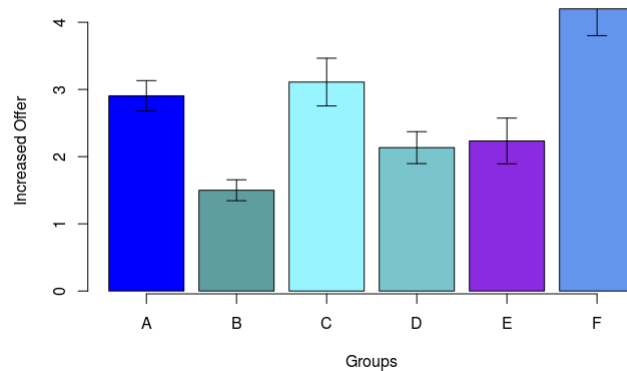


FIGURE 8.6: Increased offer by Group

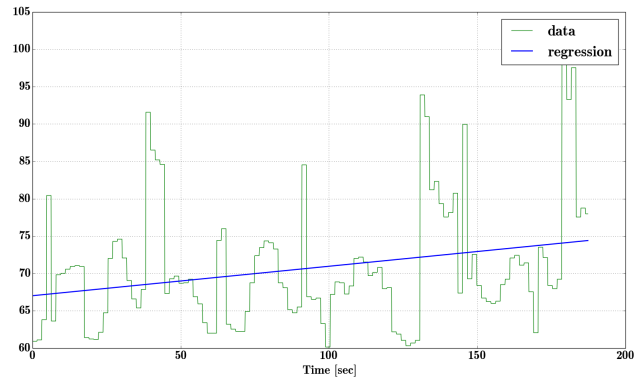
B, D, and E, presents  $p$  values of 0.015, 0.045, and 0.029, respectively. The explanation, accordingly with the Regulatory Fit theory could be that, the matching of the behavior of the robot with the user regulatory state, generated more satisfaction on the participants, which is linked with the Hypothesis 3 and the stress of the participants.

### 8.3.3 Hypothesis 3

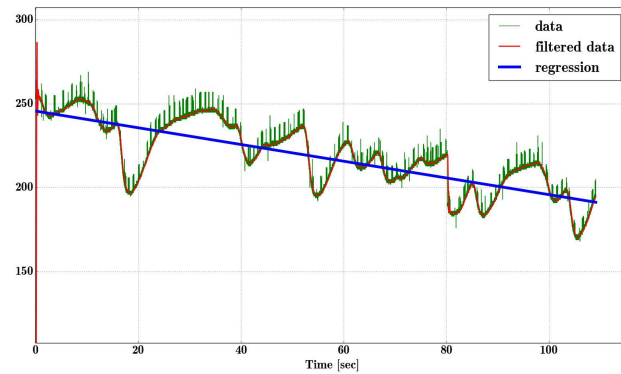
This hypothesis was half supported: only participants with Chronic Prevention Focus showed differences on the conditions.

There was only one significant difference between the groups using the measures obtained with the GSR sensor, heart rate, respiration rate, and blinking. Nevertheless, we found some correlations presented on the groups of Prevention Focus individuals. The results of these physiological signals are presented in Table 8.2. Example of these physiological signals are shown in Fig. 8.7, The Fig.8.7(a) shows an increase on Heart rate of one participant of Group D, while the Fig.8.7(b) shows decrease on skin conductance (GSR) of one participant of Group F.

The measure related with the stress level on the participants that gave significant differences was the heart rate. Participants with Chronic Prevention on the condition with the robot showing a Promotion based behavior (Group D), were the ones who showed the highest heart rate. While participants with Chronic Prevention on the condition with the robot showing a Prevention based behavior (Group F) showed the lowest heart rate. The group D presented a significant difference, applying a t-test, against the groups A (Control condition) and F (Prevention robot) with  $p$  values of 0.0451 and 0.0074,



(a)



(b)

FIGURE 8.7: (a) Increase on Heart rate of one participant of Group D. (b) decrease on skin conductance (GSR) of one participant of Group F.

respectively. This could mean, that participants with Prevention Focus interacting with the robot that did not match their Regulatory Focus, experienced more stress than participants interacting with the robot that matched their Regulatory Focus.

The correlations found on Prevention participants are associated with the GSR data. The results of the Pearson Test are shown in Table 8.3. In the control condition, participants with Chronic Prevention state (Group B) presented a positive correlation between the respiration rate and the skin conductance (GSR), which could be related with an increase on the stress. In the Robot Promotion condition, participants with Chronic Prevention state (Group D) presented a positive correlation between the Prevention score and the GSR, which means that while more dissociated the Regulatory state of the participants and the behavior of the robot, higher the stress on the participants. In the Robot Prevention condition, participants with Chronic Prevention state (Group F) presented a positive correlation between the rounds of the negotiation and the GSR, this could mean just that, with more time

TABLE 8.3: Correlations found on the physiological signals

| Resp. rate and GSR - Pearson Test       |             |         |        |        |
|---|-------------|---------|--------|--------|
| Group                                   | Correlation | P-value | t      | df     |
| B                                       | 0.9991      | 0.02698 | 23.584 | 1.0000 |
| Prevention score and GSR - Pearson Test |             |         |        |        |
| Group                                   | Correlation | P-value | t      | df     |
| D                                       | 0.9406      | 0.0171  | 4.8029 | 3.0000 |
| Rounds and GSR - Pearson Test           |             |         |        |        |
| Group                                   | Correlation | P-value | t      | df     |
| F                                       | 0.9452      | 0.0152  | 5.0168 | 3.0000 |

expended on the negotiation, more stress on the participants.

### 8.3.4 Godspeed Questionnaire

The Godspeed questionnaire, showed that the less likable behavior of the robot was the one of the control condition for the Chronic Prevention participants (Group B). The robot of the group F was rated as the less intelligent of all groups. Finally, there were no differences on the safety perception of the robot between the conditions.

## 8.4 Contributions and Conclusion

In this chapter, we presented a study on designing robot behaviors based on the Regulatory Focus and Regulatory Fit theories, in a negotiation game scenario. Our results support these theories, and open new the possibilities in human-robot interaction, in particular in social robotics, to design robot behaviors that can be of great impact in situations where the robot needs to persuade their users in certain tasks.

The results were easily identifiable for participants with Chronic Promotion Focus (their own inner strategy is to take risks in order to maximize gains). However, it was not the case for participants with Chronic Prevention Focus (their own inner strategy is to minimize losses). The opposite was obtained when analyzing the physiological signals: the significant differences were only found on Prevention participants.

Moreover, we observed that in the condition with the robot with Promotion based behavior, participants responded faster than in the other conditions. This effect could have been generated, because of the voice rate of the robot, which was the fastest of the three conditions.

In addition, it is possible that the instructions given to the participants played a role on the experiment, activating more the Promotion Focus on the participants, because they were expressed in terms of gaining the more amount of points when selling the phone to the robot.

The work described in this chapter, will be presented in the International Conference on Robotics and Automation (ICRA), Brisbane, Australia, 2018 (Cruz-Maya and Tapus, 2018).

In the next chapter, we will show the design of an adaptive behavior based on the Regulatory Focus and Regulatory Fit theories, in order to minimize the stress caused to the users, while increasing the persuasiveness of the robot by motivating the users and increasing their performance.

## Chapter 9

# Adapting Robot Behavior using Regulatory Focus Theory and User Physiological and Task-Performance Information

In Chapters 7 and 8 we presented how the Regulatory Focus Theory can be used to increase user task performance and increase the persuasiveness of the robot. In Chapter 7 we showed that it is possible to increase user's task performance in a Stroop Test, by having a robot giving instructions based on the Regulatory Focus Theory. Also, In Chapter 8 we showed the plausibility to increase robot persuasiveness by matching the robot's behavior (i.e. body gestures and speech speed) to the Chronic Regulatory Focus of the users in a Negotiation-Game Scenario. In this chapter, we wanted to go further, and we designed and implemented an adaptation system based on Regulatory Focus theory and user physiological and task performance information.

Social robots are expected to be part of the everyday life of people, which will generate interactions between humans and robots, that could have positive and negative effects on the users. For instance, robots could increment the level of stress of the users if their behavior is not appropriate. Therefore, in order to minimize the negative effects and increase robot persuasiveness, robots should behave in an appropriate manner by adapting to their users. Nevertheless, how to achieve this adaptation remains a challenge.

In the domain of social robotics and HRI, other works have been proposed to generate adaptive robot behaviors. In (Tapus, Țăpuș, and Mataric, 2008), a robot using an adaptive behavior system for post-stroke rehabilitation is presented. This work based on the relationship between the level of extroversion of the robot and the user, was adjusting three robot parameters (e.g., proxemics, speed, and vocal content). The adaptation was formulated



as Policy Gradient Reinforcement Learning (PGRL). The results showed evidence for the preference of personality matching in the assistive domain and the effectiveness of robot behavior adaptation to user personality and performance. Nevertheless, more longer sessions with the users were needed in order to validate the adaptation system.

In the context of therapy for children with autism spectrum disorder (ASD), another adaptation system was presented in (Liu et al., 2008). In this work, the robot learned the individual children preference level with respect to the configuration of robot-based basketball game. Based on that, it selected appropriate behaviors. The authors used a set of physiological measures (e.g., cardiac activity, heart sound, bioimpedance, electrodermal activity, electromiographic activity, and temperature). A Support Vector Machine (SVM) was used to classify the physiological data into affective states, and used QV-Learning to achieve the adaptation system. Results showed the effectiveness of the system.

The authors in (Mitsunaga et al., 2008) presented an adaptation mechanism based on reinforcement learning that read subconscious body signals from a human partner, and used this information to adjust interaction distances, gaze meeting, and motion speed and timing in human-robot interactions. They used the Policy Gradient Reinforcement Learning (PGRL) to achieve this adaptation. Their results showed that the robot achieved an adaptation for some parameters, but not for others. They found several issues in their study, like the difficulty of measuring true preferences. Also, for some participants, the method could neither find the gradient of some parameters nor the direction to the local optimum.

We are interested in measuring stress in the users with the main objective of adapting the behavior of the robot. Several works have demonstrated the effectiveness of Galvanic Skin Response (GSR) for measuring stress (Bakker, Pechenizkiy, and Sidorova, 2011), (villarejo2012stress).

In this chapter, we propose an adaptation system based on Regulatory Focus theory, user physiological state, and task performance information.

To the best of our knowledge, there is no previous work using Regulatory Focus and Regulatory Fit theories on an adaptive system for generating robot behaviors.

We realized a longitudinal experiment conducted with 35 participants in a game-like scenario, where a robot was trained with 24 out of the global number of the participants divided in 2 groups of 12. We used a Q-Learning algorithm based on the Regulatory Focus of the participants, user's stress,

and task performance. The model obtained was tested with 2 groups of 6 participants according to their Chronic Regulatory Focus (prevention and promotion).

## 9.1 Study Case: Adapting Robot Behavior to User Task Performance and Stress in a Game-Like Scenario

### 9.1.1 Game-like Scenario



FIGURE 9.1: Scenario with the "surgery game" and Pepper

In order to have a scenario in which we can provoke stress, and that could be repeatable with the same user without losing its interest and at the same time to be able to measure his/her performance in the task, we designed an interaction scenario using a game called "Surgery Game".

The game consists in a board containing small objects inside small holes. The players need to use tweezers in order to remove the objects. The tweezers and the borders of the holes are metallic and a "beep" sound is played if the tweezers touch the borders of the holes. We used external speakers in order to have a more stressful sound. As this game was designed to be played by children, we increased the difficulty of the game, by changing the small plastic objects with metal clips partially covered with tape, specifying the number of the object on it. We put the number of the object on a side of each hole. The objects were set-up with the numbers facing up, so that the

players could recognize them. We had the same set-up for all the players. Each object had associated a number of points that was scored based on the mean of three players before the experiment ( $points = error_{mean} * 10$ ). The objective of the game was to take out five objects with the highest number of points and with the fewest number of errors.

We put a GSR sensor <sup>1</sup> on a hand of the participants, the hand not used to play the game. This sensor gave us the feedback on the user's stress: if the signal was going up, it meant that there was an arousal increase, which leads to stress. If the signal was going down, it meant that the player was relaxing (Bakker, Pechenizkiy, and Sidorova, 2011).

The board-game was on a table, the participant was sitting on a chair, and the robot was on the other side of the table, in front of the user, as it is shown in Fig. 9.1. The board-game was connected to a Phidget21 board <sup>2</sup> in order to get the user's performance by measuring the mistakes (pliers/objects touching the borders). We used the NaoQi ROS driver to facilitate the communication between the robot and the GSR sensor and Phidget21 board that run on an external computer.

The role of the robot was to suggest to the player the objects to take out. The player had the option of following or not the advice of the robot. The behaviors of the robot are described in the next section.

### 9.1.2 Robot behavior

The robot used in this work was the Pepper robot (designed by SoftBank Robotics), which has the capabilities of Face Detection and Tracking, Automatic Speech Recognition (ASR), movement of the body and head to track the user, and Text To Speech (TTS). These capabilities are provided by the NaoQi Framework.

We designed five behaviors according to the Regulatory Focus Theory, consisting of five different body gestures and speech speeds. They can be seen as five levels on a range going from Prevention State to Promotion State. These gestures are shown in Fig. 9.2. The first behavior consisted of a closed body gesture and slow speech (70% of default speed), it is shown in Fig. 9.2(a). The fifth behavior consisted of a large body gesture and fast speech (110%), it is shown in Fig. 9.2(e). The speed of the speech increased 10% at each level, being 90% at the level 3 because the default speed of Pepper voice is already fast.

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<sup>1</sup>[http://wiki.seeed.cc/Grove-GSR\\_Sensor/](http://wiki.seeed.cc/Grove-GSR_Sensor/)

<sup>2</sup>[https://www.phidgets.com/docs21/Main\\_Page](https://www.phidgets.com/docs21/Main_Page)

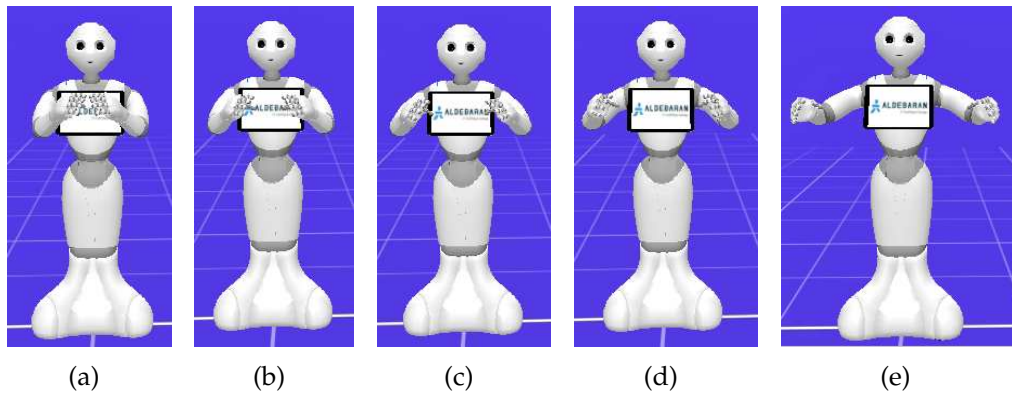


FIGURE 9.2: Robot body gestures corresponding to the 5 levels of a range going from Prevention State (a) to Promotion State (e)

The movements of the robot arms were symmetric, they were designed using the Choregraphe Software and were run by using the Module "ALAnimationPlayer" of the NaoQi Framework. All of them started from the "Stand" posture of the module "ALRobotPosture". The degrees of the robot joints, of the behaviors level 1 and 5, are shown in Table 9.1.

We used the module "ALSpeechRecognition" of the NaoQi Framework using the English language. The dictionary of the recognized words was the following: dictionary = ["yes", "no", "item one", "item two", "item three", "item four", "item five", "item six", "item eight", "item nine", "item ten", "item eleven", "item twelve", "item thirteen", "done"]. The speech recognition was paused each time the robot talked, in order to avoid self voice recognition of the robot. The recognized words were saved in the memory using the module "ALMemory", subscribing to the event "WordRecognized". Each time the robot recognized a word, we compared it to the words in the dictionary. If its associated probability valued surpassed a threshold of 30 then the

TABLE 9.1: Amplitude of the robot (right) arm of Behaviors from level 1 to 5

|                 | 1     | 2      | 3      | 4      | 5      |
|-----------------|-------|--------|--------|--------|--------|
| RElbow          | 61.8° | 62.1°  | 62.7°  | 62.7°  | 44.9°  |
| RElbowYaw       | 53.3° | 52.1°  | 52.4°  | 61.8°  | 52.1°  |
| RHand           | 0.76° | 0.89°  | 0.90°  | 0.90°  | 0.90°  |
| RShoulderPitch: | 27.6° | 29.1°  | 29.4°  | 29.4°  | 29.5°  |
| RShoulderRoll:  | -3.3° | -12.5° | -23.2° | -31.4° | -41.8° |
| RWristYaw::     | 2.3°  | 2.1°   | 2.4°   | 19.8°  | 29.8°  |

message was sent to the robot to execute the corresponding behavior. The "item seven" was not included because of bad recognition of the ASR.

The robot started the game presenting itself. At each round for taking an object, the robot proposed an object with the following speech: "I propose the item (number of item proposed)", while performing one of the five body behaviors previously presented. If the participant said "yes", then the robot answered "Great, you can take the object", if the participant said "no", then the robot asked "Then, which item will you take?". The user answered by saying the number of the object ("item one" to "item thirteen"). The robot confirmed the object by saying "Item number (object number), with (object points) points?". Then the user answers could be again "yes" or "no".

### 9.1.3 Behavior Adaptation System

We used a Q-Learning approach based on the user physiological and game-performance information, capable of generating an adapted model of robot's behavior.

The states of the Q-Learning were defined by the user stress and task performance, as follows:

1. User stressed, Good performance.
2. User stressed, Bad performance.
3. User not stressed, Good performance.
4. User not stressed, Bad performance.

In order to know the *user\_stress*, we applied a linear regression to the GSR signal, on the time the robot proposed the object to remove and the time the user said "done". If the linear regression was going up, then we considered the user as stressed, otherwise we considered the user as not stressed.

Prior to starting the training of the robot, we tested the "Surgery Game" with 3 persons. They removed each object three times. For each object, the average of the number of times the tweezers touches the metal edge of the opening (for each object) was considered as the threshold between good or bad performance for the participants in the experiment.

The actions were defined by the robot behaviors, based on the Regulatory Focus Theory. Also the robot proposed an object based on its difficulty. The actions of the Q-Learning for robot behaviors are shown in Table 9.2.

The reward of the actions was computed as the sum of the user stress and task performance. The pseudocode for computing the reward is the follow:

```

if user_stress > 0 then
    rew_stress = -0.5
else
    rew_stress = 0.5
end if
if touches < threshold then
    rew_touches = 0.5 * (1 - touches/threshold)
else
    if touches ≥ threshold then
        rew_touches = -0.5
    else
        rew_touches = -0.5 * (1 - touches/threshold)
    end if
end if
reward = rew_stress + rew_touches
    
```

The Q-Learning defines the learning function (Eq.9.1) for each pair of state/action, as follows:

$$Q(s, a) = Q(s, a) + \alpha * ((reward + \gamma Max(Q(s, A))) - Q(s, a)) \quad (9.1)$$

Where  $\alpha$  is the learning rate, and was set at 0.1, and gamma is the discount factor of future rewards, and was set at 0.9.

Also, the probability of executing the action with the highest reward was  $1 - \epsilon$ . Epsilon started with a value of 0.2, decreasing at a rate of 0.5%.

TABLE 9.2: Actions of the Q-Learning for robot behaviors

| Behavior        | Speech % | Piece Difficulty |
|-----------------|----------|------------------|
| 1 (Fig. 9.2(a)) | 70%      | Very easy        |
| 2 (Fig. 9.2(b)) | 80%      | Easy             |
| 3 (Fig. 9.2(c)) | 90%      | Neutral          |
| 4 (Fig. 9.2(d)) | 100%     | Difficult        |
| 5 (Fig. 9.2(e)) | 110%     | Very difficult   |

### 9.1.4 Experimental Design Setup

We recruited 40 participants to do the experiment. In order to know the Chronic Regulatory State of the participants, they completed the Regulatory Focus Questionnaire - Proverb Form (RFQ-PF 18 items), originally developed in French (Faur, Martin, and Clavel, 2017). We used this questionnaire, because using proverbs allow to evaluate the preferences of strategy regulation in a discrete and subtle way and it does not depend only on the personal history of the person.

The participants were divided, according to their result on the Questionnaire, in Promotion participants or Prevention participants.

### 9.1.5 Hypothesis

We formulated our hypotheses as follows:

H1. The stress of participants on the game-like scenario, will decrease with the training of our adaptive robot behavior system.

H2. The robot persuasiveness on the game-like scenario, will increase with the training of our adaptive robot behavior system.

H3. The task performance of participants on the game-like scenario, will increase with the training of our adaptive robot behavior system.

### 9.1.6 Training the robot

In order to train our model based on the Regulatory Focus and Regulatory Fit Theories, we used a group of 12 participants with Chronic Promotion State for training a model, and another group of 12 participants with Prevention State for training another model.

We explained to the participants the rules of the game and the role of the robot. Also, in order to increase their motivation on the experiment, we told them that the participant with the highest score and the fewest errors (touching the borders) would receive a prize. Before starting the experiment, they completed the Mood Higgins Questionnaire (Crowe and Higgins, 1997).

The participants took around 5 minutes to get used to the game and to the "beep" sound played each time they touched the borders of the holes with the tweezers. When they said they were ready to play with the robot, we started the experiment.

Each participant played three times the entire game. Each game consisted of removing 5 objects from the game-board. After finishing the three games,

they answered the Mood Higgins Questionnaire one more time. Also, the participants completed the Godspeed Questionnaire (Bartneck et al., 2009) (sections for Likability, Perceived Intelligence, and Perceived Safety).

### 9.1.7 Testing of the model

In order to test our models based on the Regulatory Focus and Regulatory Fit theories, we used two groups of six participants in each, matching their Chronic Regulatory State with the ones used in the training of the models. It means, a Promotion group of participants tested the model trained with the Promotion group, and a Prevention group of participants tested the model trained with the Prevention group.

The participants completed the Mood Higgins Questionnaire (Crowe and Higgins, 1997) at the beginning of the experiment and the same questionnaire and the Godspeed Questionnaire (Bartneck et al., 2009) (sections for Likability, Perceived Intelligence, and Perceived Safety) at the end of the experiment.

### 9.1.8 Measures

In order to measure the efficacy of the model generated with our system, we divided the training groups (Promotion and Prevention participants) in two subgroups each one. The first subgroup consisted of the first half of participants that trained the robot, we refer to it as Training 1 (6 participants each one). The second subgroup consisted of the last half of participants that trained the robot, we refer to it as Training 2 (6 participants each one).

The testing group for the promotion type was composed of 6 participants, and the testing group for the prevention type was composed of 5 participants.

Given the 4 states (stress-performance), presented in section 9.1.3, and the 5 actions (prevention-promotion behavior) presented in Table 9.2, after executing the actions of the robot, we did a comparison between the groups on training versus the groups on testing for each regulatory type.

We compared the stress (increased or decreased), the performance (number of points), the errors (number of touches), and the robot persuasiveness (match between the proposed object and the removed object).

GSR signals for participants non stressed and stressed participants are presented in Fig. 9.3 and Fig. 9.4 respectively.

Also we compared the results of the questionnaires (Godspeed and Mood Higgins Questionnaire).



TABLE 9.3: Q-Learning Matrix obtained by promotion participants

| States | Actions      |        |        |              |        |
|--------|--------------|--------|--------|--------------|--------|
|        | a1           | a2     | a3     | a4           | a5     |
| s1     | -0.022       | -1.000 | -0.017 | <b>1.191</b> | -0.405 |
| s2     | 0.000        | 0.119  | -1.000 | <b>0.500</b> | 0.000  |
| s3     | <b>0.716</b> | -0.234 | 0.004  | -0.073       | -0.148 |
| s4     | 0.000        | 0.000  | 0.000  | <b>0.147</b> | -1.000 |

### 9.1.9 Training the robot

We trained the Q-learning algorithm with 12 participants for each Regulatory type (promotion and prevention). Each participant played the game 3 times, each game consisted of removing 5 objects, then there were in total 15 trials per participant.

The obtained matrix of the Promotion participants is shown in Table 9.3. The algorithm learned that for promotion participants, the best action to perform was the action 4 (a4), with the only exception of the state 3 (s3), where the action 1 (a1) was the best option. These results are, at first glance, in concordance with their regulatory type, as Chronic Promotion Focus people tend to make risky decisions. The action 4 showed a behavior almost at the maximum of the promotion scale (see Table 9.2) and the robot proposing a difficult object. While action 1 was a complete prevention behavior and the robot proposing a very easy object, learned for state 3, which was a stressed participant with good performance on the previous round of the game. The rewards of the actions were based on the participant stress and performance, and there was no direct relation between the objects and the learned actions, because the participant could choose between following or

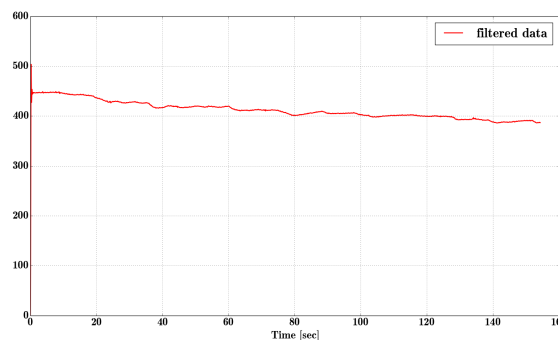


FIGURE 9.3: GSR signal of a non stressed participant

TABLE 9.4: Q-Learning Matrix obtained by prevention participants

| States | Actions      |       |              |       |              |
|--------|--------------|-------|--------------|-------|--------------|
|        | a1           | a2    | a3           | a4    | a5           |
| s1     | 0.303        | 0.477 | 0.391        | 0.000 | <b>1.293</b> |
| s2     | <b>1.715</b> | 0.000 | 0.000        | 0.000 | 0.000        |
| s3     | <b>1.084</b> | 0.128 | 0.851        | 0.981 | 0.000        |
| s4     | 0.000        | 0.000 | <b>1.113</b> | 0.000 | 0.000        |

not the robot proposition.

The obtained matrix by the prevention participants is shown in Table 9.4. The algorithm learned that for prevention participants, being in states 2 and 3, the best action to perform was the action 1, which showed the more prevention behavior and the robot proposing a very easy object. The state 2 was a bad participant performance and no stressed participant, the state 3 was a stressed participant with good performance. For the state 1, the learned action was the action 4, which showed a complete promotion behavior and proposed a very difficult object. For the state 4, which was a stressed participant with bad performance, the learned action was the action 3, which was a neutral robot behavior and the robot proposing the object with intermediate/neutral difficulty.

There were states of the Q-learning trained with prevention participants, that were not so often reached (states 2 and 4), causing a limited training on these states.

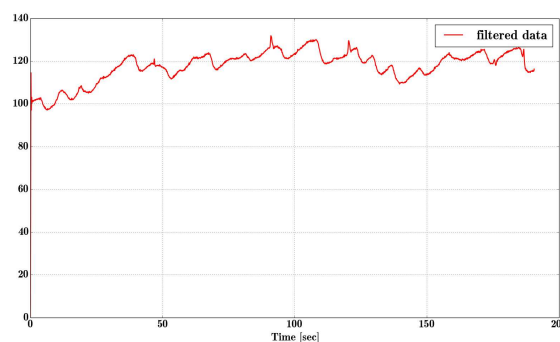


FIGURE 9.4: GSR signal of a stressed participant when removing a object from the board

TABLE 9.5: Comparison of testing and training groups - mean (std dev) for promotion participants

| Group      | Match       | Stress      | Points      | Touches     |
|------------|-------------|-------------|-------------|-------------|
| Training 1 | 0.30 (0.46) | 0.65 (0.47) | 54.6 (28.7) | 2.06(3.48)  |
| Training 2 | 0.70 (0.46) | 0.36 (0.48) | 49.7 (31.0) | 3.12 (3.95) |
| Testing    | 0.47 (0.50) | 0.45 (0.50) | 55.3 (30.3) | 2.87 (4.31) |

### 9.1.10 Testing the model

We started our analysis with omnibus ANOVA tests, in order to find interactions of the learned actions for the 4 states (stress-performance) and the stress (increased or decreased), the performance (points), the errors (touches), and the robot persuasiveness (match between the proposed object and the removed object).

#### Promotion Participants

The mean and std deviation of the persuasiveness (match), user stress, performance (points) and errors (touches) of each group for the promotion focus participants, are shown in Table 9.5.

A two-way ANOVA test with *Match* as dependent variable and *Group* and *Last\_State* as independent variables revealed an interaction between *Group* and *Last\_State* ( $p = 0.0125$ ,  $F = 4.47$ ), then we divided the groups for analyzing the effects of the actions for each *Last\_State*. We performed ANOVA tests for the data of each state, having *Match* as dependent variable and *Group* as independent variable, there was a main effect of the *Group* for

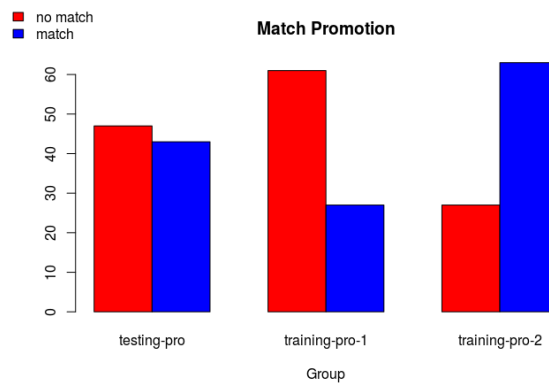


FIGURE 9.5: Robot persuasiveness for promotion participants: matching of proposed object (robot) and removed object (user)

$Last\_State = 3$  ( $p = 8.88e - 05$ ,  $F = 10.34$ ). Then, we applied a pairwise t-test to the *Match* of these groups, and we found a difference ( $p = 0.0001$ ) between the training 1 and training 2 groups. The training 2 group got more matches ( $mean = 0.42$ ,  $stddev = 0.50$ ) than training 1 group ( $mean = 0.09$ ,  $stdDev = 0.29$ ), and also training 2 group got more matches ( $p = 4.8e - 05$ ) than the testing group ( $mean = 0.03$ ,  $stddev = 0.18$ ). These results tell us that the robot persuasiveness for state 3 (user stressed and good performance) was adapting to the users on the training phase, but it was not good enough for new users.

Another main effect of the *Group* on the *Match* was found for  $Last\_State = 4$  ( $p = 0.0275$ ,  $F = 5.81$ ). A pairwise t-test showed significant differences between training 1 and training 2 groups ( $p = 0.016$ ), and between training 1 and testing groups ( $p = 0.016$ ). The training 2 group got more matches ( $mean = 1.0$ ,  $stdDev = 0.0$ ) than training 1 group ( $mean = 0.33$ ,  $stdDev = 0.57$ ), also the testing group got more matches ( $mean = 1.0$ ,  $stdDev = 0.0$ ) than training 1 group. Then, robot persuasiveness for state 4 (user stressed, bad performance) increased on the training phase and was validated on the testing phase.

The robot persuasiveness (matching of proposed object and removed object) in the testing and training groups for promotion participants is shown in Fig. 9.5, where we can see that the persuasiveness was higher on the training 2 group.

A two-way ANOVA Test with *Stress* as dependent variable and *Group* and *Last\_State* as independent variables showed no interaction between the independent variables, but there was a main effect of *Group* on the *Stress* ( $p = 0.0009$ ,  $F = 7.25$ ). Then a pairwise t-test applied on the *Stress* of these groups, showed a difference between training 1 and training 2 groups ( $p = 8.2e - 05$ ), and between training 1 and testing groups ( $p = 0.0057$ ). The stress of the users was higher on training 1 group ( $mean = 0.65$ ,  $stdDev = 0.47$ ) than in training 2 group ( $mean = 0.36$ ,  $stdDev = 0.048$ ) and than in testing group ( $mean = 0.45$ ,  $stdDev = 0.50$ ). These results, show that the behavior of the robot adapted to promotion focus participants, for being less stressful for them.

The user stress (increased or decreased after each round) in the testing and training groups for promotion participants is shown in Fig. 9.6, where we can see that the user stress was higher on the training 1 group (beginning of the training).

We applied two-way ANOVA Tests, with the same independent variables,

TABLE 9.6: Comparison of testing and training groups - mean (std dev) for prevention participants

| Group      | Match       | Stress      | Points      | Touches     |
|------------|-------------|-------------|-------------|-------------|
| Training 1 | 0.35 (0.48) | 0.50 (0.47) | 56.8 (33.8) | 2.17 (3.01) |
| Training 2 | 0.38 (0.49) | 0.50 (0.46) | 59.5 (41.3) | 3.40 (5.07) |
| Testing    | 0.50 (0.50) | 0.47 (0.33) | 54.1 (40.7) | 3.14 (4.61) |

and *Points* and *Touches* as dependent variables separately. There were no main effect and no interactions between them. Then, the robot behavior didn't had an effect on the overall performance of the participants.

### Prevention Participants

The mean and std dev of the persuasiveness (*match*), user stress, performance (*points*) and errors (*touches*) of each group for the promotion focus participants, are shown in Table 9.6.

A two-way ANOVA test with *Match* as dependent variable and *Group* and *Last\_State* as independent variables showed an almost significant main effect of the *Group* on the *Match*. Following this tendency, we applied a pairwise T-test to the *Match* of this groups, and it showed a difference between training 1 group and testing group ( $p = 0.049$ ). The *Match* was higher on the testing group ( $mean = 0.50, stdDev = 0.50$ ) than in the training 1 group ( $mean = 0.35, stdDev = 0.48$ ). These results show a small increase on the persuasiveness of the robot for prevention focus participants.

The robot persuasiveness (matching of proposed object and removed object) in the testing and training groups for prevention participants is shown

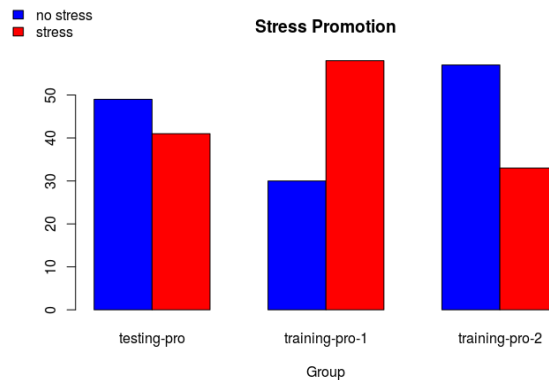


FIGURE 9.6: User stress for promotion participants

in Fig. 9.7, where we can see that the persuasiveness presented a small improvement on the testing group.

There were no differences on *Stress*, *Points*, and *Touches* between the different groups, as it can see in Table 9.5, the measures were similar in the 3 groups.

The user stress in the testing and training groups for prevention participants is shown in Fig. 9.8, here we can see an apparent decrease of stress on the participants on the testing group, but the size of this group was smaller than the others and the statistical analysis did not show a significant difference.

### 9.1.11 Godspeed Questionnaire Results

We compared the three groups and the results of each item of the Godspeed Questionnaire, using an ANOVA one-way test with *Group* as independent

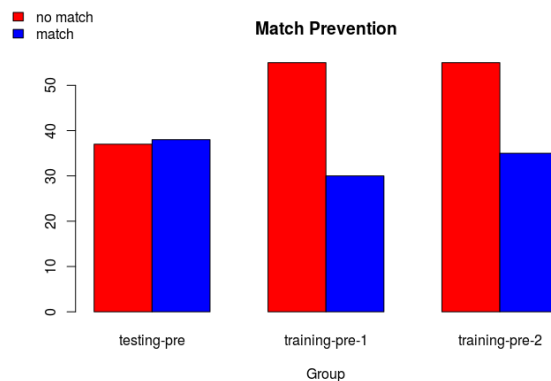


FIGURE 9.7: Robot persuasiveness for prevention participants: matching of proposed object (robot) and removed object (user)

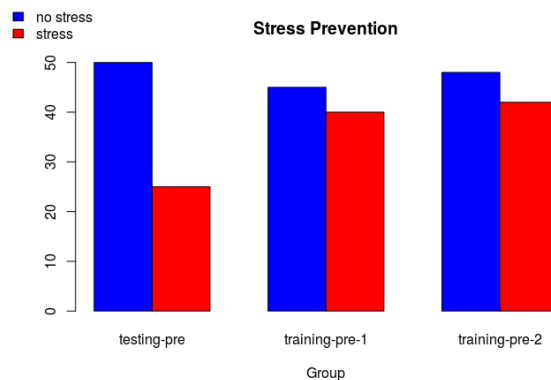


FIGURE 9.8: User stress for prevention participants

variable and the items as dependent variables. The Likert scale of this questionnaire go from 1 to 5.

For promotion participants, we found main effects of the *Group* for the items corresponding to Friendliness ( $p = 0.0385$ ,  $F = 5.08$ ), Pleasantness ( $p = 0.0101$ ,  $F = 8.47$ ), Niceness ( $p = 0.0269$ ,  $F = 5.93$ ), and Responsibility ( $p = 0.0245$ ,  $F = 6.16$ ). We applied pairwise t-test to these groups and we found statistically significant differences on the testing and the training groups.

The testing group of promotion participants found the robot very Pleasant ( $mean = 4.50$ ,  $stdDev = 0.54$ ), more pleasant ( $p = 0.01$ ) than participants in the training 1 group ( $mean = 2.66$ ,  $stdDev = 1.63$ ). They found the robot very nice ( $mean = 4.50$ ,  $stdDev = 0.83$ ), nicer ( $p = 0.027$ ) than participants in the training 1 group ( $mean = 3.00$ ,  $stdDev = 1.41$ ). Also, they found it responsible ( $mean = 4.16$ ,  $stdDev = 0.75$ ), more responsible ( $p = 0.02$ ) than participants in the training 1 group ( $mean = 2.66$ ,  $stdDev = 1.03$ ).

For prevention participants, we found main effects of the *Group* for the items corresponding to Likeness ( $p = 0.0416$ ,  $F = 4.96$ ) and Intelligence ( $p = 0.0298$ ,  $F = 5.75$ ). The testing group of prevention participants found the robot somewhat Likable ( $mean = 3.40$ ,  $stdDev = 0.89$ ), more likable ( $p = 0.034$ ) than participants in the training 1 group ( $mean = 2.33$ ,  $stdDev = 0.81$ ). Also, they found the robot somewhat intelligent ( $mean = 3.60$ ,  $stdDev = 0.89$ ), more intelligent ( $p = 0.018$ ) than participants in the training 1 group ( $mean = 2.33$ ,  $stdDev = 0.51$ ).

## 9.2 Contributions and Conclusion

In this chapter, our main contributios are the development and implementation of a method based on the Regulatory Focus Theory, user stress and user task performance, and reinforcement learning for generating a robot behavior with the goal of reducing user's stress and increasing robot persuasiveness. We implemented it on a Pepper robot. We trained our system with 24 participants, 12 for each regulatory type, and tested it with 11 participants, 6 for promotion regulatory type and 5 for prevention regulatory type.

The training of the Q-learning algorithm, used to training the robot behavior, showed to be more effective for promotion participants than for prevention participants. This could be solved increasing the number of people on the training groups, or we could increase the randomness of action selection at the beginning of the training phase, because in our case there were

states for prevention participants that were not reached so often, and the algorithm was stuck in one action and did not explore the others. The training for promotion participants explored almost all the actions, but there were also some actions not explored for the state 4. Nevertheless, this state (user stressed and bad performance) was almost not reached in the case of promotion participants, because the robot behavior caused a decrease of user stress. Then, the more iterations the more unusual that the user presented this state.

Our hypothesis 1 was validated only for promotion participants, because they showed a statistically significant difference on the user stress between testing and training groups. We think that this hypothesis was not validated for prevention participants, because the training for their regulatory type did not cover all the actions for all the states. A longer training or an increase of initial randomness of action selection would be beneficial for this regulatory type.

Our hypothesis 2 was validated for both regulatory types, because they presented an increase of robot persuasiveness. Participants accepted more the suggestions of the robot on the testing phase than at the beginning of the training.

Our hypothesis 3 was not validated, since participants didn't show any improvement on their performance, represented by the points and errors on the game. Nevertheless, the performance remained the same across the training and testing, while the stress was reduced (at least for promotion participants).

Also, the Godspeed Questionnaire supported these results, as the promotion participants found the robot more friendly, pleasant, nice and responsible than participants in the first half of the training phase. Also, prevention participants found the robot more likable and intelligent than participants in the first half of the training phase.

In conclusion, our approach of using the Regulatory Focus Theory to generate robot behaviors for minimize user stress while they user is performing a task, gave us promising results. The persuasiveness of the robot was increased and this led to decreasing the stress on the user. This is of great importance for social robots, as one of their role is to remind their users about the task they need to do, robots need to be persuasive enough to convince the users without being stressful.





## Chapter 10

# Conclusion

The focus of my thesis was mainly on human-robot interaction and consisted in studying the role of memory, personality, and regulatory focus in Human-Robot Interaction.

### 10.1 My Contributions

In the first experimental study, presented in Chapter 3, the "Social Facilitation" effect (Zajonc et al., 1965) in a Human-Robot Interaction in a game-like scenario was analyzed. In order to have a robot capable of generating a natural behavior, we implemented on a Nao robot an adaptation of the OCC Model (Ortony, Clore, and Collins, 1990) and an Episodic-Like Memory System (Leconte, Ferland, and Michaud, 2014). We used the OCC Model because we thought it was the better option for our approach, because it is a cognitive model, which in order to generate the emotions, it makes a reasoning on past events and the current context. As one of our objectives was to develop a framework capable of adapting to the users in a long-term context, we decided to include the usage of an Episodic-Like Memory system in our framework, because this is a long-term memory that is in charge of retrieving personal experiences events (Tulving, 2002).

The main contribution of our first experimental study, is the use of a robot with an emotion system facing the social facilitation effect in an interaction scenario. Results showed a tendency to reinforce the social facilitation theory, which makes us believe that this should have to be considered for companion robots where the interaction in everyday life can provoke stressful situations for the users.

The framework including the Episodic-like Memory System and the OCC Model for the Emotion System, should work with the primary users of the robot and learn through direct interaction with them. However, when the robot is also exposed to other people than their primary users, for example

relatives or friends, the robot should behave in an appropriate manner. However, in most of the cases the robot does not have enough information about past interactions. Furthermore, this situation can also happen with the primary users when unencountered situations between the robot and the user occur. For this reason, we decided to include the use of users personality in our study.

In our second experimental study, presented in Chapter 4, we analyzed the relation between user's personality and robot reminders on a set of 9 different conditions. This was of high importance to us in order to obtain information about preferences and performance of people with different personalities. We opted for the use of the Big 5 personality trait (Norman, 1963) (Digman, 1996), which is the most accepted personality trait model in the contemporary literature (Goldberg, 1993). In order to do our experiment, we developed a robot behavior to remind various tasks to the users in an office-like environment. The behavior was designed in consideration of the criteria for good reminders (Reason, 2002), and implemented in a Meka M-1 robot.

The main contribution of our second experimental study, was the evidence that supports the literature about the personality traits of extroversion and conscientiousness, and that this can be applied to Human-Robot Interaction. We found greater performance of high conscientiousness people over low conscientiousness people, and the results suggest that introverted people are more influenced to finish the task earlier than extroverted people. For these reasons, we conclude that robots could be helpful for reminding tasks to introverted and high conscientiousness people while they are working in a daily activity (by taking in consideration the factors used in the experiments, i.e., distance, height, and smile).

In our third experimental study, presented in Chapter 5, we analyzed the relation of robot's embodiment, and machine voice with user's stress. We compared the use of a computer tablet and a human voice. We also included user's personality in the analysis. In order to do this analysis, we developed a multimedia presentation in HTML and javascript based on the guide for Multimedia Learning proposed by (Mayer, 2014a), which was presented on a Kompai robot and a computer tablet to different groups of users separately. We grouped the users with respect to their personality and gender.

The main contribution of our third experimental study, was the simultaneous study of multimedia learning theory by using a robot and the effects of stress and user's personality and gender on learning. The results showed an increase of stress in the condition where the robot and synthesized voice

were used. We conclude that we need to be aware of the stress caused to the users when designing robot applications. Furthermore, we need to pay more attention to users with high level of neuroticism, who scored better on the test, but probably this was due to their anxiety, caused by the pressure made to themselves. This negative effect could have been generated by the robot's presence. Regarding the gender differences, we found that female participants did not show any significant difference on their performance under the 4 different conditions as male participants did. We suspect that this was due to their greater interest in learning about the topic proposed in the experiment.

In our fourth experimental study, presented in Chapter 6, we presented our framework based on an Episodic-Like Memory and a cognitive model of emotions (OCC) and the use of this framework to create a robot model behavior based on the personality and gender of its users. A group of participants interacted with the robot three times, in different days each time, they specified their preferences for three parameters defining the robot's behavior in a close interaction. The preferences were saved individually for each user and also grouped by personality and gender. The models created by personality and gender were tested with another group of participants, comparing with a robot behavior based on introversion/extroversion personality.

One contribution of our fourth experimental study, is the combination of the OCC model with the Episodic-Like Memory. We designed a mechanism to use the events on memory to generate the emotion of "Hope", which at the same time is used to ponder memory events on the Episodic-Like Memory. Another contribution of this chapter is the evidence, that an adaptive model based on personality and gender for robot behaviors could give better results than a predefined robot behavior, even if this behavior is based on theories like the Similarity Attraction Theory or the Complementary Needs Theory.

The models created using personality traits and gender, performed well to predict user's preferences. Nevertheless, we also wanted to increase motivation and performance of people when they are performing a task. For this reason, we opted to use the Regulatory Focus Theory, which is more linked with performance.

In our fifth experimental study, presented in Chapter 7, we analyzed the relation between user's performance and the regulatory focus theory in a Human Robot Interaction. We presented an experiment where a robot gave

instructions to complete a Stroop Test to a group of participants. The participants were divided in groups with respect to their score on a test of Regulatory Focus. The robot presented three conditions, in the first and control condition, the robot did not include any regulatory strategy. In the second condition the robot gave instructions that included a Promotion oriented strategy, while for the third condition it included a Prevention oriented strategy.

The main contribution of our fifth experimental study, is the evidence that Regulatory Focus Theory can be used in Human-Robot Interaction to improve users' performance. We found that Promotion participants performed better when the robot presented a Promotion strategy than when the robot presented a Prevention strategy. Also, we found that Prevention participants performed better than Promotion participants on the condition with the Prevention robot. Besides, we validated our hypothesis that users would be more stressed on the conditions where the robot strategy does not match the Chronic Regulatory state of the participants.

In our sixth experimental study, presented in Chapter 8, we evaluated different robot behaviors based on the Regulatory Focus and Regulatory Fit theories, in a negotiation game scenario in a Human-Robot Interaction. We proposed the use of different gestures and speech speeds, in order to minimize the user's stress and increase user's performance. We presented an experiment with three different robot behaviors: robot control condition, robot Promotion based behavior, and robot Prevention based behavior. The behavior of the robot (Pepper robot) was presented to the user in a negotiation game scenario. Also, participants were divided in groups based on their Regulatory States: in Promotion and Prevention groups, respectively. In the negotiation game scenario, the participants played the role of the seller, and the robot played the role of the buyer, where the robot followed a cooperative-competitive strategy.

The main contribution of our sixth experimental study, is the validation of the Regulatory Focus and Regulatory Fit theories in the context of Human-Robot Interaction. We found that participants with Chronic Promotion Focus effectively gave more concessions to the robot when it presented a Promotion based behavior. Also, participants with Chronic Prevention Focus did not give more concessions to the robot on the negotiation game when it presented a Prevention behavior, but their increase on the offer was the highest of all groups. Our hypothesis related to the stress has been linked to the Regulatory state and was only supported by participants with Chronic Prevention, on the condition with the robot showing a Promotion based behavior,

where they showed the highest heart rate of all groups.

Our results showed the importance of including Social Psychology Theories, such as the Big 5 Personality traits and the Regulatory Focus, when designing robot behaviors for companion robots. Nevertheless, these theories have a number of variables to be taken in consideration, and context can have an impact on the results. For this reason, we think that an adaptive behavior is a better option, for generating an appropriate behavior, as we presented in this thesis.

## 10.2 Limits and Future Work

Our work presented several limits but at the same time several opportunities to explore the fields of emotions, memory, personality, and regulatory focus in Human-Robot Interaction.

The implementation we did of the OCC Model was not extensive, as the model itself has some limitations. The OCC model is more extensive than we thought at the beginning of our work. Many variables of this model, are of psychological nature, and defining an algorithmic implementation can be difficult (e.g., variables such as sense of reality or psychological proximity). Furthermore, we implemented only a limited set of emotions, a large set of other emotions remains to be explored, as well as other scenarios where they can be applied. For instance, we used the emotion of hope, so as to let the robot generate a better greeting behavior according to the user's preferences, in a similar way the emotion of gratitude could be used to generate a gratitude behavior in a more appropriate context.

The Episodic-like Memory system, was only linked with the emotion of Hope, which gave us good results on generating an adaptive robot behavior. As explained before, we could take advantage of the different emotions available in the OCC Model to create various robot behaviors as a function of the situation and the context. Nevertheless, this topic needs to be more studied, in order to know which emotion applies to each situation. Also, we found that combining the OCC model variables with the Episodic-like memory can be different depending on the emotion to be generated. Besides, the Episodic-like Memory can be more exploited, using different contexts. For example, we could create a model for greeting the users in the morning, another for greeting the users in the evening, where the preferences of the users can be different. This could be easily implemented on the robot without changing

anything in our framework, only adding the time where the episode is happening.

Regarding the personality traits, we did some experimental studies, mainly focusing on Extroversion and Conscientiousness, as they were the most appropriate in our context related to user's preferences and performance. Nevertheless, the others traits remained unexplored by us, with the only exception of Neuroticism, of which we found a relation with performance. The traits of Agreeableness and Openness could have interesting effects on Human-Robot Interaction.

Last but not the least, the use of Regulatory Focus and Regulatory Fit theories gave us good results in increasing user motivation and performance. We are among the firsts using these theories in Human-Robot Interaction.

As future work, we would like to design and implement an adaptive model of robot behavior based on the Regulatory Focus, and the Episodic-like Memory system, and the OCC model. This adaptive model behavior should adapt to the user performance and stress, in order to increase user's performance and decrease user's stress.

## Appendix A

# Evaluation Documents

### A.1 Big Five Questionnaire

<https://goo.gl/bGm3Ab>

### A.2 Regulatory Focus Questionnaire - Proverb Form English

<https://goo.gl/oPeh6p>

### A.3 Godspeed Questionnaire - Sections 1-3

<https://goo.gl/Wz9BcK>

### A.4 Game-Like "Find the pair" Scenario Post-Questionnaire

<https://goo.gl/forms/3TNI4KjvXu>

### A.5 Office-Like Scenario Post-Questionnaires

<https://goo.gl/zQfaK5>

### A.6 Multimedia Scenario Post-Questionnaire

<https://goo.gl/QNmnrk>



## **A.7 Learning Users' Preferences Post-Questionnaire - Training**

<https://goo.gl/QNmMrk>

## **A.8 Learning Users' Preferences Post-Questionnaire - Testing**

<https://goo.gl/nNtHrJ>

## Appendix B

# Publications List

1. Ferland, François, Arturo Cruz-Maya, and Adriana Tapus (2015). “Adapting an hybrid behavior-based architecture with episodic memory to different humanoid robots”. In: *Robot and Human interactive Communication, 2015. RO-MAN 2015. The 24th IEEE International Symposium on*. IEEE.
2. Cruz-Maya, Arturo, François Ferland, and Adriana Tapus (2015). “Social Facilitation in a Game-Like Human-Robot Interaction Using Synthesized Emotions and Episodic Memory”. In: *Proceedings of the International Conference on Social Robotics*, pp. 164–173.
3. Cruz-Maya, Arturo and Adriana Tapus (2016a). “Influence of Users Personality on Task Execution When Reminded by a Robot”. In: *International Conference on Social Robotics*. Springer, pp. 829–838.
4. Cruz-Maya, Arturo and Adriana Tapus (2016b). “Teaching nutrition and healthy eating by using multimedia with a Kompai robot: Effects of stress and user’s personality”. In: *Humanoid Robots (Humanoids), 2016 IEEE-RAS 16th International Conference on*. IEEE, pp. 644–649.
5. Cruz-Maya, Arturo, Roxana Agrigoroaie, and Adriana Tapus (2017). “Improving User’s Performance by Motivation: Matching Robot Interaction Strategy with User’s Regulatory State”. In: *International Conference on Social Robotics*. Springer, pp. 464–473.
6. Cruz-Maya, Arturo and Adriana Tapus (2017). “Learning Users’ and Personality-Gender Preferences in Close Human-Robot Interaction”. In: *Robot and Human interactive Communication, 2017. RO-MAN 2017. The 26th IEEE International Symposium on*. IEEE.

7. Cruz-Maya, Arturo and Adriana Tapus (2018). "Negotiating with a robot: Analysis of Regulatory Focus Behavior". In: Proceedings of the International Conference on Robotics and Automation. IEEE.

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**Titre :** Le Rôle de la Personnalité, de la Mémoire et de l'Attention Réglementaire sur l'Interaction Humain-Robot

**Mots clés :** Interaction Homme-Robot, robotique social, apprentissage machine, attention réglementaire, adaptabilité de comportement du robot, et personnalisation.

**Résumé :** Dans le domaine de l'Interaction Homme-Robot, et plus particulièrement dans le domaine de la robotique sociale, les robots compagnons font de plus en plus partie de notre vie quotidienne et ont un grand potentiel pour aider les gens dans leurs activités quotidiennes. Avoir des robots qui nous aident dans nos activités quotidiennes conduit à la nécessité de les doter de capacités sociales afin d'adapter leur comportement à leurs utilisateurs, leur environnement et leurs tâches. Néanmoins, comment réaliser cette adaptation reste un défi.

Dans cette thèse, nous essayons de répondre à des questions comme "Comment effectuer de l'apprentissage de long durée et l'adaptation

pour une interaction homme robot personnalisée?" et "Quel est le rôle de la personnalité, de la mémoire et du regulatory focus dans l'HRI. Nous présentons plusieurs études expérimentales, où nous testons notre système, et où nous analysons le lien entre les traits de personnalité de l'utilisateur humain et le comportement du robot.

Nous concluons que les sujets étudiés dans cette thèse: la personnalité, la mémoire et le regulatory focus, doivent être inclus dans la conception des comportements des robots, afin d'avoir des robots plus efficaces sur les tâches persuasives, et comportements moins stressant pour leurs utilisateurs.

**Title :** The Role of Personality, Memory, and Regulatory Focus on Human-Robot Interaction

**Keywords :** human-robot interaction, social robotics, machine learning, regulatory focus, personalization, robot behavior adaptation and customization

**Abstract:** In the field of Human Robot Interaction, and more specifically in the social robotics field, companion robots are more and more part of our daily lives and they have a great potential for helping people in their daily activities, especially in tasks that need one-on-one interaction. Having robots helping us with our daily activities leads to the need of endowing them with social capabilities in order to adapt their behavior to their users, environment, and tasks. Nevertheless, how to achieve this adaptation remains a challenge.

In this thesis, we would like to address the following research questions, "How to achieve lifelong learning and adaptation for

personalized Human-Robot Interaction?" and "What is the role of personality, memory, and regulatory focus in HRI?". We present several experimental studies, where we test our system, and where we analyze the link between the human user's personality traits and robot's behavior.

We conclude that the topics investigated in this thesis: Personality, Memory and Regulatory Focus, have to be included in the design of robot behaviors, in order to have more efficient robots on persuasive tasks, and less stressing behaviors to their users.

