# Proto-communication, Social Bonding and Persuasiveness for Minimally Designed Robots Scaffolded by Non-Expert Trainers

（ミニマルデザイン型ロボットと人との原初的コミュニケーションの構築に関する研究）

July, 2016

Doctor of Engineering

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Date of Submission:
平成　2016　年　07　月　15　日

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**Abstract**

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| Title of Thesis 博士学位論文名 | Proto-communication, Social Bonding and Persuasiveness for Minimally Designed Robots Scaffolded by Non-Expert Trainers |

(Approx. 800 words)
(要旨　1,200 字程度)

In order to build social robots that can coexist with human beings, it is necessary to understand the mechanisms of how communication protocols are developed in human-robot interactions. Our main goal was to explore how a communication protocol can be established incrementally between a human and our minimally designed robots. The first robot that we consider in our work is called Sociable Dining Table (SDT). SDT integrates a dish robot put on the table and behaves according to the knocks that a human emits. To achieve our goal, we conducted two experiments: a human-human experiment (Wizard-of-Oz) and a human-robot interaction (HRI) experiment. The aim of the first experiment was to explore how people build a protocol of communication. Based on the first experiment, we suggested an actor-critic architecture that simulated in an open-ended way the adaptive behavior which we determine in the first experiment. After that, we demonstrated in the HRI experiment how our actor-critic architecture enabled the adaptation to individual preferences in order to obtain a personalized protocol of communication.

However, one of these challenges that we encountered after that with our robot is in the difference between the user's retained mental model consisting of the instructions triggering the robot's different behaviors and the robot's previously taught instructions by the user. More specifically, we remark a divergence between what was remembered by the non-expert user or believed taught to the robot in a previous HRI instance and what was actually taught to it. This divergence could lead to a waste of time when the robot is reused before it could be used effectively to achieve a task. Some users may not have the patience to reteach the robot a new version of instructions if they realize that they have forgotten previous version. Some non-expert users may not even be aware that they changed the instructions previously taught to the robot and this triggers different behaviors in the robot.

During the HRI, we remarked that the formed CP was not only personalized to the pair of the non-expert user and robot, but also to the HRI instance. This means that the CP changed each time

the human started a new interaction session with the SDT. The main reason behind the change was the non-expert users' forgetfulness of the previously established communication protocol (PECP) and their issuing of a different set of new instructions to the SDT rather than maintaining the old instructions and continuing to teach the robot new skills.

Thus, one of the challenges that we investigate is how we can modify the way the minimally designed robot communicates back to the human so that the CP could be maintained and time wasted constructing a new CP could be avoided. We describe feedback strategies combining inarticulate utterances (IUs) with the minimally designed robot's visible behaviors, to trigger an increased remembrance of the PECP.

The results provide confirmatory evidence that using IUs combined with the minimally designed robot's visible behaviors assist in driving non-expert users to maintain the PECP and avoid time wastage, negligence of the robot or task achievement failure.

We show also that the key point that made participants cooperate with the robot when it uses the IUs is the social bonding that users may feel towards minimally designed robots. To investigate so, we considered another robot called ROBOMO. ROBOMO is a mobile robot that uses IUs and gestures to form a communication protocol along with the human during the HRI.

Finally, we show also that for some users which we call them though-minded users (users that do not feel the social bonding towards the robot), it is necessary to consider the combination of different persuasive strategies so that we can convince them to continue using the robot even if some breakdowns are encountered during the PECP reuse.

# Table of contents

# List of figures

# List of tables

# Chapter 1

# Introduction

In this chapter, we introduce a number of important issues regarding the behavior based robotics concept, the ecological psychology, the ecological robotics, the challenge of scaffolding HRI when the teacher is a non-expert user as well as the different breakdowns that the interaction may face in such case.

Mitigating these breakdowns may help to maintain a long-term communication protocol and affords the interaction with the chance to become aesthetically more convenient for the human.

However, mitigating breakdowns can be insufficient to guarantee a long-term interaction with humans. Another dimension which we assume could be convincing enough for the human to keep on using the robot, is the attachment or broadly speaking the social bonding. Four factors may help measuring the social bonding which we intend to present in more details in the coming paragraphs: the attachment, the commitment, the belief and the involvement.

Also, we straddle the line under a very important factor that it is the robot's behavior style: for example a funny robot or a proactive robot, etc.. Such styles include a range of behaviors that should be displayed for the human by the robot. For example, combining eye-gaze with gestures and along with some specific jokes in order to assume that we have for example a funny robot. So instead of adding incrementally the behaviors so that we can explore the effect of so on the HRI, we could create combinations of behaviors in order to verify whether a specific behavior style may increase social bonding.

Social bonding could evolve for some people while it is not the case for example for cold-hearted people, that it is why we assume that the robot should afford more attention for this kind of people. When an error occurs while the non-expert user is scaffolding the robot's behaviors or reusing the previously established communication protocol, the robot should exhibit a specific behavior style that may guarantee the human to be persuaded when an error occurs. Errors could be described in this context as dissonant informations that are contrary to the human's preconceptions. That it is why, for people who persue always consonnant ideas, such a situation (when an error occurs during the HRI) could be threatening and leads quickly to the learned helplessness if the robot was not persuasive enough. That it is why, another important issue which we suppose that we will discuss in here is the concept of persuasive robotics.

## 1.1 Behavior-Based Robotics

Behavior-based robotics or behavioral robotics is an approach in robotics that focuses on robots that are able to exhibit complex-appearing behaviors despite little internal variable state to model its immediate environment, mostly gradually correcting its actions via sensor-motor links. The concept of behavior based robotics was introduced in the mid 1980s, and was championed by Rodney Brooks [1] and others. It consists on building ready-to use controllers such as a controller of obstacle avoidance. A resulting interaction between the robot and it surroundings is just the consequence of switching among controllers in response to environmental changes. It seems to be that the robot's behaviors are environment-centered to make the robot looks like behaving optimally and not in any case taking care of any special social norms such as proximity or turn taking protocols, etc.. Due to the limitations concerning the amount of internal representation that the robot following behavior-based paradigm should afford to include the social norms, a robot that adopts the behavior-based robotics could fail to be integrated in the society with humans.

## 1.2 Ecological Psychology

As the behavior-based robotics consisting on making the robot looks smart even though it does not include taking account of the social norms could fail to make the interaction natural and intuitive enough for the human while interacting with a social robot, we should find out another paradigm that consists on taking into account the social attitudes and the behavior norms. We assume that ecological psychology could help on studying the environment and the human-human interaction before that we implement any controller so that we could extract the special norms needed to be added on the robot's controller as well.

The term ecological originated in the field of biology and seems to be very adjacent to social areas such as social psychology and the studies of perception. For example, Kenneth R. Hammond highlighted a special issue named "ecological validity" [2] while Gibson [3] discussed the "theory of ecological perception". Eco-social psychology, then, can be defined as an approach to this science that investigates how mind and behavior are shaped in part by their natural and social habitats and how natural and social habitats are in turn shaped partly by mind and behavior. The main goal of this approach is to delineate how individuals and social ecologies define each other [4]. Thus, there are no controllers that could be designed without taking into account people's ecologies and more specifically social norms and daily natural laws of interaction even if they are not optimal.

## 1.3 Ecological Robotics

The study of sensory guided behaviors in living animals has become of general significance not only for scientists working in neuroscience and computational neuroscience but also for scientists working in robotics and distributed artificial intelligence, who were using unfortunately functional principles generated from the study of living animals as models to build computer based automata that display complex sensorimotor behaviors. Our research effort, which follows these lines, is tied together by concepts from eco-social psychology as well, to help generating an intuitive natural human-robot interaction that it is social.
Many researchers were interested to this concept of ecological robotics such as Grémillet et al [5], Stirling et al [6], Pfeiffer et al [7], etc.. Most ecological robots to be used in are mobile, and can be classified according to: the equipment they carry, their size, where they operate, their mobility and autonomy. The factor of minimal design is very important in this context to avoid the emergence of complex patterns that the robot could use and may lead to abnormalities such as a combination of words generated by trial and error and which could lead to an inconvenient situation if the robot's resultant speech is mean-less.

## 1.4 Minimal Design

Minimal Design Policy is first proposed by Matsumoto et al., who conclude that the robot's appearance should be minimized in its use of anthropomorphic features so that the humans do not overestimate or underestimate the robot's skills [8]. By minimal design, we mean eliminating the non-essential components and keep only the most fundamental functions. We expect that in the future minimally designed robots will be affordable. People will use such minimally-designed robots for many tasks such as cleaning, and here we may mention Roomba the robot [9] or to engage more with autistic children through therapeutic sessions of interaction while cooperating with Keepon the robot [10], etc.
Minimal design policy is applied to develop many other robots such as Muu [11], ROBOMO [12], CULOT [13], etc. The simple nature of minimally designed robots allows humans to

interact easily with such robots on a daily basis. On the other hand, we must pay attention to sociability and adaptation factors. In fact, interacting with an affordable minimally designed robot may represent the first experience of a human interacting with a robot. This, leads us to assume that people will possibly have high expectations about the robot's adaptive capabilities.

## 1.5 Non-Expert Users Scaffolding Ecological Social Robots

Scaffolding is the process by which a human organizes a new skill into manageable steps and provides support such that a child could achieve something that they could not achieve independently [7] [14].

An important characteristic of a good learner is the ability to learn both on one's own and by interacting with another. Children are capable of exploring and learning on their own, but in the presence of a teacher they can take advantage of the social cues and communicative acts provided to accomplish more. For instance, the teacher often guides the child's search process by providing timely feedback, luring the child to perform desired behaviors, and controlling the environment so the appropriate cues are easy to attend to, thereby allowing the child to learn more effectively, appropriately, and flexibly.

If we try to apply the scaffolding in the human-robot context then the human must teach the robot on real time and in a dynamic way. Dynamic scaffolding exists as well in human daily interaction with others as an example, one can cite the child-caregiver interaction. Dynamic scaffolding in daily life corresponds to the notion that adults create a learning situation that is of the right level of complexity for the learner. The adult adjusts dynamically to make sure the child is working within the zone of proximal development. One way to describe this is that the teacher creates "micro worlds" for the learner to master parts of the task in isolation before moving on, providing safety and intermediate attainable goals [15]. For example, with language parents first treat anything as conversational speech, but eventually they raise their expectations, scaffolding the child's conversational abilities [16].

Prior works have pointed out how supervision or more clearly dynamic scaffolding might benefit a machine learner such as a robot [17] [18] , however, for robots to realize their transformative potential, they need to be able to efficiently learn how to perform challenging tasks from humans who, although experts in the tasks their teaching, may have little expertise in autonomous robotics or computer programming. Therefore, there is a great need for new methods that facilitate the interaction between human teachers who are not expert in computer programming and learning minimally designed robots.

The feedback that the human provides during such interaction can take many forms, e.g.,

reward and punishment [19] [20], advice [21], guidance [22], or critiques [17]. Within them for example, learning from rewards generated by a non-expert trainer observing the robot in action promises to be a powerful method for non-expert users in autonomous robots to teach the robot to perform challenging tasks. However, how to make the robot learn most efficiently from such non-expert trainers is still under-addressed.
Intuitively, when learning from non-expert users, the robot's performance depends critically on the efficiency of the interaction between the robot and non-expert trainer. It also depends on the information within the feedback provided by the robot trainer. Therefore, we consider how the interaction between the non-expert trainer and the robot should be designed to reduce the trainer's effort or cost to train the robot to perform a task well. Previous studies [23] showed that the way that the robot interacts with the non-expert trainer can greatly affect the trainer's engagement and the robot's performance and that the interaction between the robot and the non-expert trainer should ideally be bi-directional.

## 1.6 Mitigating Scaffolding Breakdowns

Minimally designed robots that operate in the real world could make mistakes once taught by non-expert trainers because such trainers could have high or low expectations, they may afford the robot with wrong instructions since they are confused about the needed input. In fact minimally designed robots has a low number of sensors and actuators to make it affordable. However, this may lead to mis-processing of the information by non-expert users because they are used to the world of multimedia and the easy processed information. Thus, those who design and build systems will need to understand how to provide best ways for robots to mitigate those mistakes. We need to consider how to mitigate breakdowns in services provided by minimally designed robots. Such robots that provide a personal service through HRI create interdependence between the robot and the user. Prior research suggests that the nature of this interdependence and the robot's design can affect people's responses to system errors [24]. Non-expert trainers may feel a loss of control when they do not understand why the robot fails [25]. In one study, participants blamed their robot partner more when the robot was human-like rather than machine-like [24]. In another study, the more autonomous a robot was, the more people blamed it for failure, and explaining the reason for the failure did not help much [26]. People may have high expectations of robotic services that complicate their experience where there is a service breakdown and while interacting with a minimally designed robot. That it is why it is important to mitigate service breakdowns when non-expert trainers are interacting with non-minimally designed robots so that the interaction may look aesthetically more convenient and the taught knowledge or what we call in our works communication protocol could be maintained on a long term basis.

## 1.7 Emotions Promote Belongingness

Emotions help people get along better. Mostly, people's emotions promote their ties to others. Forming social bonds is linked to positive emotions [25] [27]. The fact that emotions promote belongingness is yet another important instance of our general theme that what happens inside people serves what happens between people and robots. Emotions help promote good interpersonal relations. The link between emotion and behavior is far from clear, but social bonding that emerges thanks to this linking influences thinking and learning. In fact, social bonding makes up a feedback system that helps people process information about the world and their own actions in it in a better way so that the communication could be maintained [28]. A long-standing communication protocol held that social bonding undermine rational and make people be more flexible with other agents. That it is why, social bonding may help developing an acute sense of belonging to the robot and this is worthy to be investigated so that we can verify whether positive emotions may evolve while interacting with minimally designed robots so that social bonding may emerge and may guarantee that humans will continue using the robot on a long term basis.

## 1.8 Prosocial Behavior: Reciprocating Others' Noble Acts

Social bonding may emerge once we link positive emotions with convenient behaviors. So, if we assume that a robot could display the right behaviors that induce positive emotions, there is then a high possibility that social bonding could evolve. To create positive emotions a robot could offer help for the human. Offering help (prosocial behavior) to the human by the robot may activate what we call reciprocity. Reciprocity is defined as the obligation to return in kind what another has done for us. Folk wisdom reorganizes reciprocity with such sayings as "You scratch my back and I will scratch yours". Reciprocity norms are found in all cultures in the world [29].

If I do something for you and you don't do anything back for me, I m likely to be upset or offended and next time around I may not do something for you. If you do something for me and I don't reciprocate I am likely to feel guilty about it. People are designed by nature to belong to a system based on fairness and social exchange. As one sign of the importance of fairness to human nature, the feeling that one has no value to others-that you are a taker rather than a giver- is a major cause of depression [30]. To be sure, there are plenty of obnoxious people who take more than they give, but most of them don't see themselves that way. People who do see themselves as taking more than they give may become depressed. To avoid depression, people may seek to contribute their fair share. Consequently, if we suppose that we are seeking behaviors creating positive emotions, one of the prominent behaviors that may lead to the emergence of such positive emotions are prosocial behaviors that could be afforded by robots so that humans feel positive emotions. Further, they can even reciprocate so with a happy mood. Consequently, not only social bonding is boosted here but also a positive long-term interaction.

## 1.9 Persuasive Robotics

Psychological studies have shown that people who lack emotions (often because of brain injuries or other problems) are not really better off in terms of thinking and learning. And social bonding that may emerge for common people to afford the chance to interact with a robot a longer time could be not be possible for people who lack emotions or in a lighter version for people who are cold-hearted. If there are no emotions felt than there will be no social bonding with the robot and thus the human-robot interaction (HRI) is threatened because such people have no counter factual thinking [31].
If we go to the point when we highlighted that faulty robot's behaviors could occur because of the scaffolding mediocre quality of non-expert trainers and we add to that the fact that social bonding cannot evolve for such cold-hearted (utilitarian) trainers, we could easily see that we need to add a robot's mechanism that it is based on logical arguments to convince such utilitarian people that they should continue interacting with the robot.
As for common people, anxiety when their preconceptions are defeated can be considered as the "shadow of intelligence" because it helps them to plan ahead and avoids taking unnecessary risks [32]. Planned behavior is related to explicit attitudes. Explicit attitudes are controlled by conscious evaluative responses. Now, when interacting with a robot and an error occurs, we cannot determine whether the human (whatever is his character: cold hearted or relational) will use the explicit or the implicit attitude. The implicit attitude can activate implicitly a spontaneous behavior. Such implicit attitude are automatic and non-conscious evaluative responses.
According to that, and since we are not sure whether implicit or explicit attitude will take control of the situation, social bonding could be helping but also if some implicit negative attitudes are encoded on the human's cognitive miser, it could be difficult to convince the non-expert trainer (whether he is relational or cold-hearted (called also utilitarian)) to continue using the robot. The only solution left is to enable the robot to convince the human

on the proper time to continue the interaction which means that we need to make the robot more persuasive.

## 1.10 Thesis question and contributions

With the previous motivations in mind, this thesis focuses on many questions that can be summerized as follows: The general problem of learning from human reward is previously undefined. This thesis gives an operational methodology of what we term the ecological social information processing for proto-communication patterns extracted on-line while the non-expert trainer is dynamically scaffolding the robot and how can we mitigate robot's service breakdowns that occur because of the scaffolding mediocre quality to guarantee a maintain of the communication protocol on a long term basis. Maintaining the same communication protocol does not guarantee that people will continue using the robot, that it is why a primer interest that we highlight is the key role that attachment or broadly speaking social bonding could play to motivate people continue using the robot. However, if the behavior that the human activates once there is an error is related to implicit attitudes, the behavior cannot be planned and the reactive evaluative answer once an error occurred during the HRI cannot be predicted and even can be difficult to be changed. That it is why, persuasion is another specific issue that we need to address too in our thesis.
In addressing this question, this thesis yields these core contributions:

### 1.10.1 Communication Protocol Establishment

Mutual adaptation is the key concept for this first study while we explain how a Woz experiment may help extracting the key patterns that help building communication protocol incrementally and how it is possible for humans to preserve some chunks of the communication protocol when they reuse the robot on a post-interaction instances.

### 1.10.2 Increase of Communication Protocol Recall

Here we mention about the general problem of proposing an implicit feedback that may increase the human's awareness when he is about to change the pre-established communication protocol during post-interaction instances. This thesis gives an operational methodology of what we term the implicit and visible feedback combination to enhance the human's recall of the communication protocol without causing any face-threatening act. As a consequence, gracefully mitigating the HRI breakdowns leads to a maintain of the communication protocol on a long term basis.

### 1.10.3 Increase of the Social Bonding

This thesis introduces ROBOMO framework, which directly addresses the thesis question of how can we integrate in a minimally designed robot robot's visible behaviors with the inarticulate utterances so that we increase the social bonding which is a motivator to maintain a long term interaction with a social robot.

### 1.10.4 Problem definition of A Standardized Method to Measure Social Bonding

Included in the thesis are directives for how to measure social bonding , accounting for four factors that Hirschi's define as for the social bonding measurement in general. We expose a case-study of the usage of such standardized tool measuring social bonding to make the right decisions concerning some of the issues that are related to the social robot's design.

### 1.10.5 Problem definition of the Cognitive Dissonance Encountered When A Breakdown Occurs While Interacting with A Social Robot

In this thesis, we empirically examines numerous plausible techniques for persuasion to guarantee a long term interaction with social robots even when some breakdowns are faced while interacting with robots and even when we consider that implicit attitudes or utilitarian people are concerned with the HRI.
In our work, we try to test out some social and factual based persuasive strategies that may help overcoming the cognitive dissonance and elaborate a positive counter attitudinal behavior which is in this context consists on keeping on interacting with the robot.

# Chapter 2

# SDT: Meaning Acquisition Exploration in Knock-Based Proto-Communication

## 2.1 Introduction

As robots move from the research lab to the real world, it is interesting that users, including those without programming skills, can teach robots customized behaviors [33][34]. If sophisticated methods were developed in order to allow users to transfer their knowledge, we may be able to guarantee long-term communication and mutual understanding. Developing robots with mutual understanding skills and exploring the meaning acquisition process in the human-human interaction is a cornerstone to build robots which can work alongside humans. By using human adaptation capability adequately, robots are capable of adapting to humans and will be easily adaptable as well. Such a process can commonly be observed in a pair who can communicate smoothly, such as a child and a caregiver.

Understanding how a caregiver behaves with a child is required to achieve key ideas about the behaviors, that can be used to design intuitive robots [35][36][37][35]. Many issues have been of interest to the HRI community, such as how children learn to talk [38], grasp an object [35], and navigate [39], etc. Understanding how such issues occur helps roboticists building intuitive robots. During a child-caregiver communication scenario, the child and the caregiver try to adapt to each other using a limited number of communication channels which they initially do not master in the same way. Incrementally, they become familiar to each other's patterns of communication. The meaning decoding of each other's behavior is no more difficult for both parties. In fact, each party implicitly infers the meanings of the other party's most commonly used patterns and links the most often used patterns to the context of the interaction. Such linking leads to an implicit formation of

Fig. 2.1 A participant interacts with the Sociable Dining Table

(patterns-meanings) cartography, which in our study is called a "communication protocol". A non-expert user and a minimally designed robot also try to customize a communication protocol which depends on the patterns emerging from limited communication channels that are not mastered in the same way during the initial communication stages.

In this vein, the purpose of this study is to explore how non-expert users can cooperate with a minimally designed robot in order to acquire a communication protocol. The challenge is to investigate how people aggregate communication patterns. We want also to investigate how to adequately take advantage from the adaptation ability of humans in order to enable our minimally designed robot SDT to adapt to new situations during a novel interaction scenario that integrates minimal communication channels. Understanding how to take advantage from the human's adaptation strategy helps us to tailor a control model for minimally designed robots that have a minimal number of communication channels. The final designed control model has to guarantee the establishment of flexible communication protocols just as in the child-caregiver interaction context.

Therefore, we draw a scenario inspired from the child-caregiver interaction and opt for knocking as the only one communication channel used by humans. Knocking is a novel communication channel that had not been used in a similar task. This guarantees that the user and the robot have the same amount of knowledge about the communication scenario. Thus, to have a successful interaction both parties need to adapt to each other. To explore how the adaptation occurs, we conduct our first experiment. It is a human-human (H-H) experiment (Figure 2.1). For each instance of interaction during the H-H experiment, we engage two participants. The first participant is the one that knocks on the table while watching the robot moving on the table (room (A)). The second participant is the one remotely controlling the robot according to the knocking sounds. Thereby, the robot is controlled via

an interface. The second participant is located in another room (room (B)).
Both parties have to cooperate in order to make the robot visit different checkpoints marked on the table. We informed each new pair (knocker-controller) that the robot can use 4 behaviors (going forward, going back, going left, going right). Based on this experiment, we want to investigate whether the task can be achieved using our only communication channel. In the case of a successful interaction, we want to explore what are the stages that the communication went through and what are the best adopted practices that led to the emergence of a communication protocol? After that, we want to implement in the robot the components and the functionalities that may guarantee to make our robot adaptive. Finally, we conduct another experiment (HRI experiment) to verify whether our robot was adaptive like in the H-H experiment. Also, we compare the H-H and the HRI experiments in terms of performance, emergent communication protocols, and the way the task is solved in each experiment.

## 2.2 Related Work

Adaptation is a term referring to the ability to adjust to new information and experiences, track the new facets of the environment and adopt the most convenient strategies based on the sequentially gathered information. Many studies point out the robot and human's adaptation to each other as being a very attractive and promising solution for the HRI [40][41]. Robot and human's adaptation to each other consists of the fact that if the human changes his behavior, the robot must adapt to this new behavior. Humans also have to change their behavior patterns to adapt to the robot's new proposed behaviors during an instance of an HRI [40]. Yamada et al.[42] investigate the capability of the human and the agent to detect each others' state of mind based on few social cues such as facial expressions [43]. The concept of adaptation is explored in many other HRI studies [44][45][43].

Some studies use many modalities integrated into the robot [46][47][48] in order to design an adaptive artifact. Other studies [49][50] examine how a speaking robot can infer the adequate speech by combining words to particular contexts through observing different situations. Kanda et al. use the robot Robovie in HRI studies to investigate children's interaction in a museum [51] and a school [52]. Thomaz et al [53] investigate the active learning to refine the robot's knowledge where multiple types of queries are used by the robot to demand an explicit spoken answer facilitating the robot's concept learning process. Subramanian et al [54] use the explicit answer of Pacman game users concerning the best interactive options that they imagine are effective for the agent teaching. These interactive options are learned in an offline mode and introduced later into the robot. These studies [52][51][54][50] explore the explicit verbal communication to implement adaptive systems while the meaning can be inferred in real time implicitly based on the behavioral interaction. We do not address the general problem of multimodal communication channels and instead we focus on a minimal communication channels concept which we expect can guarantee the emergence of simple communication patterns and is suitable for minimally designed robots.

Minimal Design Policy is first proposed by Matsumoto et al., who conclude that the robot's appearance should be minimized in its use of anthropomorphic features so that the humans do not overestimate or underestimate the robot's skills [8]. By minimal design, we mean eliminating the non-essential components and keep only the most fundamental functions. We expect that in the future minimally designed robots will be affordable. People will use such minimally-designed robots for many tasks such as cleaning, and here we may mention the Roomba robot [9] or to engage more with autistic children through therapeutic sessions of interaction while cooperating with Keepon the robot [10], etc.

Minimal design policy is applied to develop many other robots such as Muu [11], ROBOMO [12], CULOT [13], etc. The simple nature of minimally designed robots allows humans to interact easily with such robots on a daily basis. On the other hand, we must pay attention to sociability and adaptation factors. In fact, interacting with an affordable minimally designed robot may represent the first experience of a human interacting with a robot. This, lead us to assume that people will possibly have high expectations about the robot's adaptive capabilities.

In addition to humans having a natural tendency to forget quickly, there are not exact details of how an interaction occurs and what are the instructions used. For this, a human attempts to come up with any similar instructions to solve the problem. A similar phenomenon occurs in the human-pet interaction when the human forgets the exact instruction taught to the pet [55]. Interestingly, the human in that case does not recognize the difference and the pet tries to grasp the meaning incrementally in order to satisfy the human's request. In this context, we believe that robots need an extra capability which enables them to grasp the meaning of the newly introduced instructions and satisfy the human's new request. Kiesler [56] concurs with our point of view while he confirming in his studies that a minimally designed robot has to integrate a process which makes it adaptive [57]. Thus, one contribution of this work is to determine how a minimally designed robot can incorporate an adaptive process that helps establishing a communication protocol with non-expert users and adapt to their different communication patterns.

To achieve the above goal, we chose to conduct a WOZ experiment to explore how a communication protocol can be established between the users and a minimally designed robot. It is a well-known principle in robot design, that the roboticist should involve humans early in the design process, rather than in the final evaluation phase [58]. Many HRI studies [59][60][61] use the WOZ experiment in order to test early aspects of the robot's design. We agree with the fact that WOZ can help in exploring the best features which can be later incorporated in the robot's design. Also, we believe that robots are not sufficiently advanced to interact autonomously with people in a socially appropriate way. Therefore, we started our study by conducting a WOZ experiment that helped exploring the best practices humans adopt in order to establish a communication protocol. Based on the first experiment, we gained some insights in order to incorporate in our robot's architecture the best adopted practices that can get along with people's communication patterns in the context of the SDT interaction. Finally, we attempted to validate our robot's architecture through an HRI experiment in order to compare the HRI performance to the WOZ experiment performance.

We start by exposing the architecture of the SDT in section 3. In section 4, we explain our H-H experiment. In section 5, we explain our proposed architecture. Finally, in section 6 we validate our minimal architecture based on an HRI experiment.

## 2.3 Architecture of the SDT

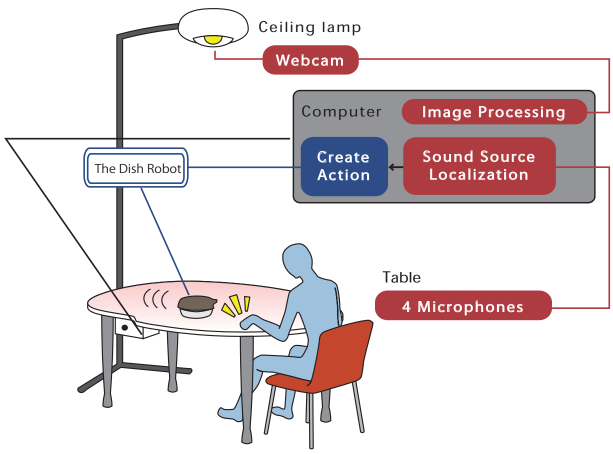


Fig. 2.2 The overall architecture of the SDT: The human's knock is detected by four microphones while the robot executes the different behaviors using the servomotor.

Our system consists of a webcam to compute the robot's positions and its angle of orientation. The robot's coordinates are used only for further analysis purposes (Figure 2.2). The robot uses four microphones to localize the knock's source based on the weighted regression algorithm [62]. It communicates with the host computer through Wi-Fi using a control unit (a macro computer chip (AVR ATMEGA128)) and employs a servomotor that helps to exhibit the different behaviors: right, forward, left and back. Finally, five photo reflectors are utilized to automatically detect the boundaries of the table and avoid falling (Figure 2.3).

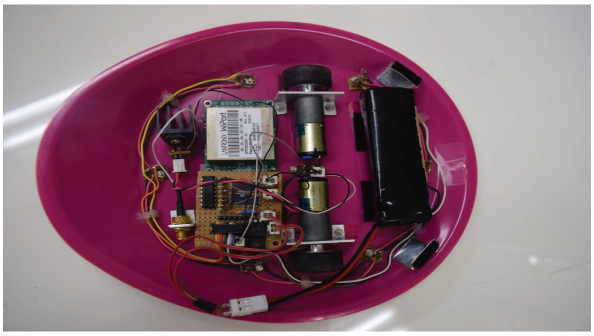

Fig. 2.3 A close-up picture showing the inside of the SDT robot.

## 2.4 Experiment 1: Human-Human Interaction

We expect that H-H experiment allows the envisioning of future useful features that can be integrated into the robot's architecture in order to make our minimally designed robot SDT adaptive .

### 2.4.1 Experimental Setup

Each time we conducted an instance of the H-H experiment, we gathered a new pair of participants and assigned the first one to the role of a knocker while the other to the role of a controller. The knocker was the one that has to knock on the table in order to help the robot visit different points marked on the table. The controller was the one that has to remotely control the robot based on the knocking.

Before a knocker enters the experimental room ($A$), the instructor told him the purpose of the experiment is to help the robot to land on different checkpoints marked on the table. The knocker did not know that a human controlled the robot when he knocked, while the controller did not know that another person emitted the knocking. This helped us to simulate convenient conditions guaranteeing that any possible emerging communication protocol would emerge if we were in a real HRI. Also, by exploring how gradually a communication protocol emerged we may find out the key ideas that we needed to integrate in order to elaborate a convenient adaptive architecture for our robot. The knocker was located in a first room ($A$) and can visualize the robot as well as all the checkpoints on the table. In another room ($B$), the controller remotely controlled the robot while listening to the knocking without seeing the predefined checkpoints. The controller could only visualize an interface showing the robot moving since he was in another room. We isolated each party in a different room in order to make sure that no eye contact or facial expressions could be exchanged between both parties. The instructor told the controller that he needed to listen to the knocking, guess

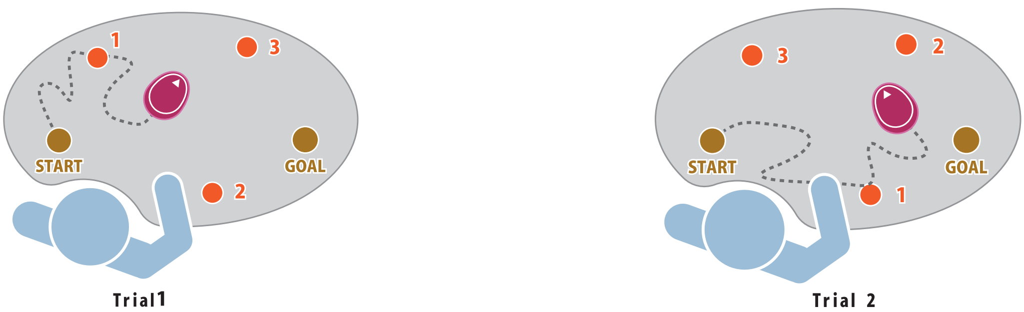


Fig. 2.4 In the first trial (left), the controller tries to understand the knocker's patterns of knocking in order to move the robot into five decided places on the table (start, 1, 2, 3, and goal) by means of knocking patterns. In the second trial (right), we change the place of the former points on the table, and then the knocker and the controller have to exploit the emerged rules of communication of the first experiment to guide the robot into the newly defined points.

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the meaning and then choose the convenient direction based on his own opinion. Finally, after the experiment ended we interviewed both participants (knocker and controller). Importantly, we asked them to describe their experience with the robot through simple phrases.

In the first trial, the pair (knocker-controller) had to cooperate in order to lead the robot to different sub-goals (Figure 2.4). In the second trial, we changed the coordinates of the former points and the pair (knocker-controller) had to cooperate to reach the new check points. We chose several different configurations. At each time the goal position and the intermediate check points were changed. This may guarantee that the participants were not accustomed to the configuration. Also, it helped us confirming the pairs (knocker-controller) used their adaptation abilities and the emerging communication patterns rather than memorizing the different transitions that helped to achieve the task in the previous trial. There are two trials, each lasting 20 minutes[1] and video-recorded. During each new trial, the new controller and the new knocker try to cooperate in order to achieve the task. We did not indicate for the pairs that they must follow a special knocking strategy so that they interact in a natural way with the robot and we can also see whether they aggregated some redundant patterns to form a communication protocol with the robot.

### 2.4.2 Subjects

We hired thirty Japanese students (ages: Mean (M)=20.2, Standard Deviation(SD)=2.0 [years]) from different universities. Sessions 1 and 2 were performed with thirty subjects

[1] We estimated this period based on a previous pilot study.

(eighteen males and twelve females). A written informed consent was obtained from all the subjects.

### 2.4.3 Results

After the experiment was finished, we attempted to analyze the interaction scenarios in order to verify whether a communication protocol was established between the knockers' knocking patterns and the chosen actions. We also attempted to detect the components that led to the possibly emergent communication protocols.

We analyzed the video data by annotating with a video annotation tool called ELAN. Two coders, one of the authors and one volunteer, analyzed the behavioral data captured in the video camera using the same coding rules for the first and the second trials. We picked ten data sets arbitrarily from our entire data set which were coded based on rules. We calculated the average of Cohen's kappa to investigate the reliability. As a result, we confirmed that there was a reliability with $\kappa = 0.98$

#### Evaluation of the Command-Like and the Continuous-Knocking Patterns based on the Videos

We remarked that there are 2 types of patterns: continuous - knocking patterns and command-like patterns. Command-like pattern consisted of combining each behavior with a different combination of knocks (e.g., 2 knocks for *Forward*). Continuous-knocking was used when there was contiguous interruptions in the robot's behavior[2]. We counted the number of both types of patterns based on the coded data for each participant and for the two trials. We noticed that there was a significant usage of the command-like patterns (90.26% of the patterns were command-like during trial 1 compared with 89.47% of the patterns during trial 2).

To verify whether the usage of command-like was statistically significant, we conducted a t-test between the number of command-like patterns and the number of continuous-knocking patterns used by the participants during the trial 1 : *(t=6.973, d.f=14, p-value $<$ 0.01)* and trial 2: *(t=4.750, d.f=14, p-value $<$ 0.01)*. For both t-tests, we found that there was a significant difference between both types of patterns usage during trials 1 and 2, highlighting that participants were trying to simplify the input in each interaction cycle for the robot.

Participants confirmed through most of their answers that they wanted to simplify the input for the robot. One of the participants indicated : "...I was confused initially but as

[2] Continuous-knocking was related to the presence of contiguous disagreements about the shared rules, and we defined a disagreement state in the section 4.3.2

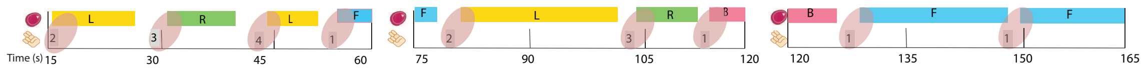


Fig. 2.5 The first (left), second (center) and final (right) time segmentations of an extract of the interaction from the first experiment where in the first line we have action executed by the robot: F, R, L and B stands for forward, right, left and back behaviors; in a second line, the corresponding knocking patterns such as 2 or 3 knocks, etc.; and in a third line the time progress in seconds.

time goes by I start to compose simple redundant input to get the regular intended output...", another participant confirmed that: "...The robot is smart, while there are some repetitive combinations between my knocking and the chosen actions and thus I started to track the best knocking that led to the convergence to stable combinations. It has to be slow modulated knocking..."

#### Evaluation of an Interaction's Scenario

To investigate the different stages of pattern emergence, we tried to explore the flow of the interactions. A sample flow of pair 15 is depicted in Figure 2.5 where in grey we have the knocking while the corresponding action is represented by the colorful line.

Figure 2.5 shows that most of the time when the controller received a knocking pattern, the latter waited a small period of time in order to choose the behavior that he thought the most appropriate for the received knocking pattern. As an example, we could see that when the knocker emitted a new knocking pattern, the controller stopped for a while to think before attributing the behavior according to his own assumptions (all red circles). Consequently, if the knocker was satisfied with the controller's choice he would not knock, otherwise the knocker would knock again before 2 seconds (based on the knocker's reaction time (KRT) distribution: [mean:1.93 ;sd:0.12] seconds) elapsed in order to implicitly indicate to the controller that he must change direction again. Some exploration was adopted [55-57s] when encountering a new pattern. In fact, the controller chose the correct behavior for the new pattern (1 knock) even if the pattern was encountered for the first time. Interestingly, if we track the mapping of the knocking patterns and the robot's behavior, we find that in some occasions the rule was maintained for several times such as for the pattern (2 knocks) when it was associated with the *left* behavior ([15-16s], [45-47s] and [79-81s]), and the (3 knocks) pattern when it was associated with *right* behavior ([30-32s] and [102-104s]). However, at other times there was a change in the rule combination such as when (1 knock) was initially associated with the *forward* behavior ([55-57s]) and later with the *back* behavior ([114-116s]).

When the controller and the knocker shared the same assumption about one of the knocking pattern-robot's behavior combinations that was maintained over time we call that state an "agreement state". If the combination knocking pattern-robot's behavior changed over time we call that state a "state of disagreement". The participants were then blending incrementally in a trial-and-error process the agreement and disagreement states in order to establish shared rules organizing the communication.

### Adaptation's Evaluation based on the Agreement and Disagreement States Comparison

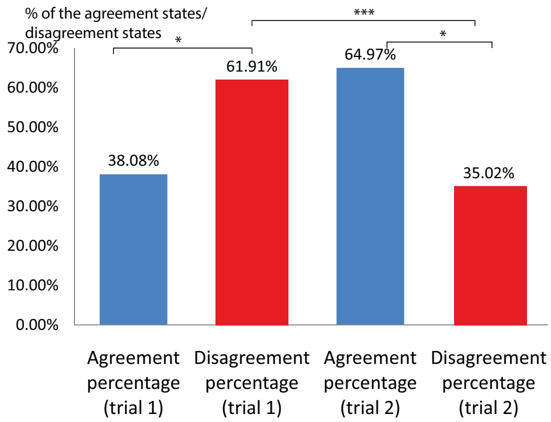



Fig. 2.6 The percentage of agreement and disagreement states during the experiment 1.

To evaluate the different pair interactions' convergence toward a stable protocol, we counted the number of the agreement and the disagreement states based on the coded data for both trials and all the pairs. We computed the t-test between the agreement and the disagreement states of the trial 1. The results were significant with *($t$=2.242, d.f=14, p-value=0.033<0.05)*. Figure 2.6 shows the percentage of the agreement states (blue color) as well as the percentage of the disagreement states (red color) during the trials 1 and 2 [3]. By examining the percentage of the agreement and disagreement states of the trial 1, we deduced that during the trial 1, disagreements (61.91%) were more significantly frequent than agreements (38.08%) (Figure 2.6).

We computed the t-test between the agreement and the disagreement states of the trial 2. The results were also significant with *($t$=2.067, d.f=14, p-value = 0.048 < 0.05)*. By displaying the percentage of the agreement and disagreement states of the trial 2, we deduced that during trial 2, agreement states (64.97%) were more significantly frequent than

[3] As an example, the percentage of agreement states= number of agreement states/(number of agreement states+number of disagreement states)

disagreement states (35.02%) (figure 2.6). Finally, we calculated the t-test between the trial 1 and 2 disagreement states. The results were statistically significant with *(t =2.948, d.f=14, p-value = 0.006<0.01)*. By displaying the percentage of the trial 1 disagreement states (61.91%) and the percentage of the trial 2 disagreement states (35.02%), we deduced that during the trial 1, disagreement states (61.91%) were significantly more frequent than disagreement states of the trial 2 (35.02%) (Figure 2.6).

#### Comparison of the Task Completion Time in Trial 1 and Trial 2

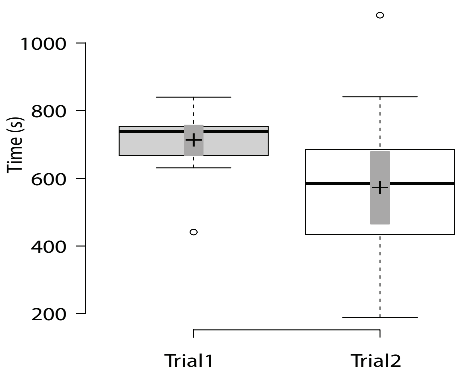



Fig. 2.7 Task completion time distributions during trials 1 and 2 (experiment 1).

The time to reach the different sub-goals was estimated based on the videos. The distribution of the task completion time datasets of the trial 1 (first boxplot in grey) and 2 (second boxplot in white) are represented in Figure 2.7. Results showed that there is a decrease on the task completion time during the trial 2 (Figure 2.7). A t-test showed that there was a statistically significant difference between the task completion time of the trial 1 and 2 with *(t=2.143, d.f=14, p-value=0.041<0.05)*. This highlighted that although during the second trial we changed the configuration by changing the point coordinates (which may imply that the pairs would have to adapt to each other again in a new context), the pairs succeeded on achieving the task more quickly during the trial 2.

#### Cooperative Communication for the Task Achievement

To study the incremental adaptation to each others' behaviors, we calculated the number of confusion states and the remedial knocking states. Figure 2.8 helps to understand the meaning of these two practices. As you may see in the Figure 2.8, the robot executed initially the forward behavior, and when the controller detected that he received a knocking pattern (2 knocks in red), he picked left as a new behavior. Within a few milliseconds, we can see that the controller changed the behavior to back. We called such situation a state of confusion since the controller changed the behavior after recently choosing an action and without being prompt by any knocking. As a response the knocker, composed of a remedial knocking pattern (2 knocks in orange: the same previous knocking pattern) so as to help the controller overcome the situation by resuming with the previous executed behavior. The presence of states of confusion indicated that the controller tried to establish the rules of communication but may go through some confusing states. Consequently, the knocker also tried to adapt to the controller's state of confusion by composing a remedial knocking pattern.

We calculated the Pearson correlation between the confusion states and the remedial knocking of the first and second trials. The value of R during the trial 1 is 0.6149 with (P-Value from Pearson (R)=0.014; d.f=13; The result was significant at $p<0.05$) and during the trial 2 with R value (P-Value from Pearson (R)=0.00019. d.f=13; The result was significant at $p<0.01$). This meant that there was a tendency for high confusion states values went with high remedial knocking values (and vice versa). Consequently, if the confusion states occured more frequently, the knocker would try to cooperate most of the time with the controller in order to maintain the rules which he thought they were shared between him and the controller.

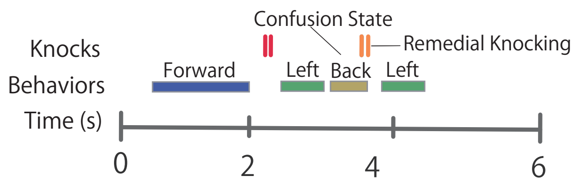



Fig. 2.8 A scenario showing an example of a state of confusion and a remedial knocking pattern.

### Communication Protocol Analysis

The subjective results and the previously discussed objective analysis showed that there was a cooperation between the knockers and the controllers in order to adapt to each other and establish communication protocols. To visualize the emergent communication protocols, we used the correspondence analysis. Correspondence analysis is an exploratory technique that helps analyzing the two-way frequency cross-tabulation tables containing measures of correspondence between the knocking patterns and controllers' interpretations of these patterns. The results provide information which is similar in nature to those produced by Factor Anal-

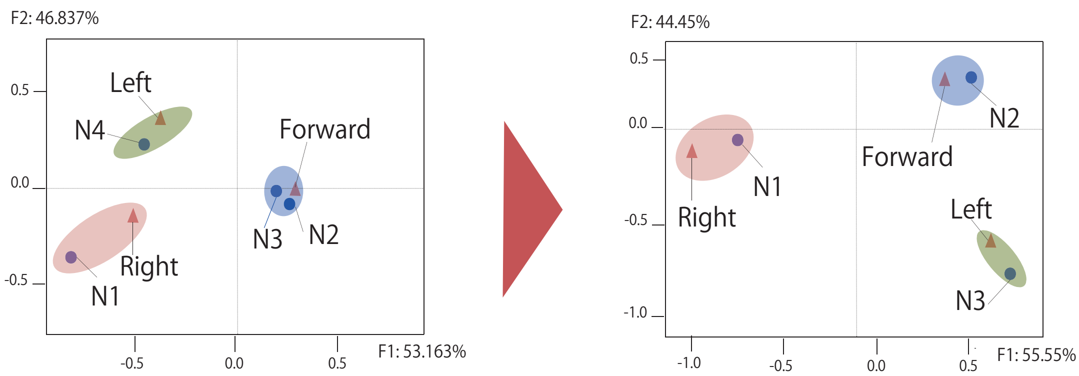



Fig. 2.9 Correspondence analysis for both trials for the pair 9 (Left: first trial, Right : second trial) in the first experiment where Ni represents the knocking patterns ; e.g., : N2 represents 2 knocks.

ysis techniques, and they allow us to explore the structure of our two variables (knocking patterns and controllers' interpretations to these patterns) by means of derived dimensions F1, F2,.., Fn.

To understand how the dimensions are derived, we need to consider the Chi-square statistic for two-way tables like in our example (knocking patterns and the related controllers' interpretations of these behaviors). Any deviations from the expected values (expected under the hypothesis of complete independence of the knocking patterns and the controllers' interpretations) would contribute to the overall Chi-square. Thus, another way of looking at correspondence analysis is to consider it a method for decomposing the overall Chi-square statistic (or Inertia=Chi-square/Total N) by identifying a small number of dimensions in which the deviations from the expected values can be represented. This is similar to the goal of Factor Analysis, where the total variance is decomposed, so as to arrive to a lower-dimensional representation of the variables that allow us to reconstruct most of the variance matrix of variables.

For a matter of illustration, we chose to depict the associations between knocking patterns and controllers' interpretations of pair 9 (Figure 2.9). It appeared that based on the two-way frequency table associating the pair 9's knocking patterns to the controllers' interpretations, we had two derived dimensions. With a single dimension F1 (trial 1: F1=53.163% and trial 2: F1=55.550 %) as we represented in Figure 2.9 53.163% in trial 1 and 55.550% in trial 2 of the inertia can be "explained," that is, the relative frequency values can be reconstructed from a single dimension and reproduced 53.163% of the total shi-square value (and, thus, of the inertia) for the case of our two-way table. Two dimensions allowed us to explain 100% of the data with F2 (trial 1: F2=46.837% and trial 2: F2=44.450% (Figure

2.9).

Based on the (Figure 2.9(right)), we remarked that *right* behavior is materialized by 1 knock, *forward* was represented by 2 and 3 knocks, and *left* by 4 knocks. In the second trial (Figure 2.9(left)), the protocol was slightly ameliorated where we could see a clear categorization of *forward* that was represented by only 2 knocks while *left* was represented by 3 knocks and *right* was always represented by 1 knock.

#### Performance Evaluation based on the Convergence Metric Values

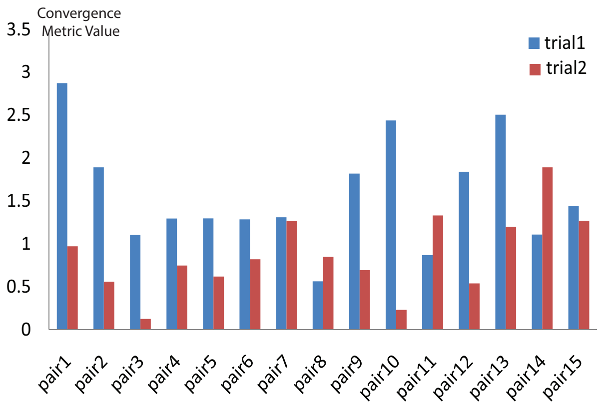



Fig. 2.10 The convergence metric values of the first and second trial (experiment 1).

We wanted to explore whether there was a statistically significant difference between the convergence level to a stable communication protocol during trials 1 and 2. For this purpose and based on the correspondence analysis results, we calculated the Euclidean distance between each of the robot's behaviors (red triangles as presented in the Figure 2.9) and the different patterns (blue circles as presented in the Figure 2.9). Thus, for each behavior we calculated the *n* possible Euclidean distances (assuming that we have *n* possible patterns). After that, we picked for each behavior the most minimal distance. We summed up the 4 most minimal distances and the resultant value afforded information about the most minimal distance that the pair knocker-controller achieved to form stable rules. We called this value the convergence metric which evaluated the system's performance. We repeated the same procedure for the 15 pairs and for the two trials.

We computed the t-test between the convergence metric values of the trial 1 and 2 which revealed significant differences: $t=2.503$, $d.f=14$, $p\text{-value} = 0.018<0.05$. We displayed the results of the trial 1 and 2 convergence metric values where in blue we had the convergence metric values of the first trial and in red the convergence metric values of the second trial (Figure 2.10). Figure 2.10 showed that 12 out of the 15 pairs (80%) succeeded in reducing the convergence metric values during the second trial, indicating that the pairs were closer to the convergence to stable protocols' formation.

Table 2.1 The test of independence (Chi-Square) between the knocking patterns and the robot's behaviors as well as the Cramer's V (CV) values of the trial 1 (experiment 1)

| Pairs | *Chi-square* | *CV* |
|---|---|---|
| Pair1 | $\chi^2$=55.515, d.f=18, ***p-value$<$0.01 | 0.446 |
| Pair2 | $\chi^2$=21.978, d.f=18, p-value=0.233 | – |
| Pair3 | $\chi^2$=12.394, d.f=9, p-value=0.192 | – |
| Pair4 | $\chi^2$=18.6565, d.f=12, p-value=0.097 | – |
| Pair5 | $\chi^2$=9.828, d.f=12, p-value=0.631 | – |
| Pair6 | $\chi^2$=26.345, d.f=15, **p-value=0.035 | 0.331 |
| Pair7 | $\chi^2$=10.222, d.f=3, **p-value=0.017 | 0.698 |
| Pair8 | $\chi^2$=2.475, d.f=6, p-value=0.871 | – |
| Pair9 | $\chi^2$=12.634, d.f=8, p-value=0.125 | – |
| Pair10 | $\chi^2$=50.068, d.f=18, ***p-value$<$0.01 | 0.590 |
| Pair11 | $\chi^2$=5.528, d.f=9, p-value=0.786 | 0.166 |
| Pair12 | $\chi^2$=19.307, d.f=9, **p-value=0.023 | 0.529 |
| Pair13 | $\chi^2$=9.828, d.f=12, p-value=0.631 | – |
| Pair14 | $\chi^2$=14.215, d.f=2, ***p-value$<$0.01 | 0.823 |
| Pair15 | $\chi^2$=17.071, d.f=18, p-value=0.518 | – |

**Consistent Protocol Formation Evaluation**

To statistically measure the relationship between the knocking patterns and the different behaviors, we computed the test of independence (Chi-square) between the knocking patterns and different behaviors as well as the Cramer's V-Values. Table 2.1 and 2.2 exhibited the results of the first and second trials for the different participants. Based on the Table 2.1 we deduce that 7 out of 15 pairs (46.66% of the pairs) succeeded in establishing a stable communication protocol during trial 1, where the chi-square values were significant for 7 pairs, with a Cramer's V-Values ranging from 0.331 to 0.823, indicating a strong relationship between the knocking patterns and the controller's interpretations of these patterns. We noticed that during the trial 2 (Table 2.2), the number of pairs that succeeded in establishing a communication protocol increased to 11 out of 15 pairs (73.3% of the pairs) with high Cramer V-Values, indicating that there was also a strong relationship between the knocking patterns and the controller's interpretations of these patterns. Consequently, we deduced that gradually there was a strong relationship between the knocking patterns and the controller's interpretations of these patterns.

Table 2.2 The test of independence (Chi-Square) between the knocking patterns and the robot's behaviors as well as the Cramer's V (CV) values of the trial 2 (experiment 1).

| Pairs | *Chi-square* | *CV* |
|---|---|---|
| Pair1 | $\chi^2$=31.640, d.f=12, ***p-value=0.002 | 0.568 |
| Pair2 | $\chi^2$=28.119, d.f=8, ***p-value<0.01 | 0.404 |
| Pair3 | $\chi^2$=0.877, d.f=2, p-value=0.645 | – |
| Pair4 | $\chi^2$=10.297, d.f=12, p-value=0.590 | – |
| Pair5 | $\chi^2$=4.422, d.f=4, p-value=0.352 | – |
| Pair6 | $\chi^2$=18.033, d.f=8, **p-value=0.021 | 0.308 |
| Pair7 | $\chi^2$=4.6, d.f=4, p-value=0.331 | – |
| Pair8 | $\chi^2$=8, d.f=2, **p-value=0.018 | 0.9 |
| Pair9 | $\chi^2$=12.036, d.f=4, **p-value=0.017 | 0.501 |
| Pair10 | $\chi^2$=26.813, d.f=12, ***p-value=0.008 | 0.829 |
| Pair11 | $\chi^2$=22.610, d.f=6, ***p-value<0.01 | 0.408 |
| Pair12 | $\chi^2$=17.714, d.f=4, ***p-value<0.01 | 0.859 |
| Pair13 | $\chi^2$=23.517, d.f=6, ***p-value<0.01 | 0.637 |
| Pair14 | $\chi^2$=34.476, d.f=15, ***p-value=0.003 | 0.384 |
| Pair15 | $\chi^2$=32.799, d.f=9, ***p-value<0.01 | 0.594 |

### 2.4.4 Discussion

We started with a H-H experiment to evaluate the knockers' and controllers' adopted behaviors that led to the emergence of communication protocols. Understanding both parties' strategies facilitated for us the tailoring of a control model that could be integrated into the robot and may lead to a similar flexible communication protocol formation.

**Evaluation of the Command-Like and the Continuous-Knocking Patterns based on the Videos**

Based on the coded videos, we remarked that the communication was patterned. It was crucial for the pairs to scaling the problematic to a small number of entry states (1 knock, 2 knocks, etc.). The use of continuous-knocking was a way to overcome the contiguous disagreements. By examining the percentages and the t-test results, we remarked that there were potential trend to use the command-like more frequently during the trials 1 and 2. The objective of the pairs was to minimize the expected infinite horizon of states to a small number of states in order to easily track each of the states successful combinations with the controller's interpretations of these patterns. Thus, during the communication protocol establishment, users restricted the number of states to facilitate inferring the communication rules (even if we do not impose for the human a way of an interaction with the minimally designed robot).

### Evaluation of Interaction Scenarios

Interrupting the controller's executed action was associated with the presence of knocks (negative reward for the controller), while no knocks implied the controller was doing well (positive reward). Based on this trial-and error process, the pairs were incrementally establishing communication protocols by mainly going through multiple agreements and disagreements about the shared rules as the Figure 2.5 showed.

### Adaptation Evaluation based on a Comparison of Agreement and Disagreement States

Based on the t-test results and Figure 2.6 we concluded that disagreement states decreased significantly from trial 1 to trial 2. We deduce also that the agreement states were significantly inferior than the disagreement states during the trial 1 in addition to the fact that the same thing occurred during the trial 2. These results suggested that even though the pairs normally had to adapt again to each other during trial 2 in order to share the communication rules (since we had a new configuration with different checkpoint coordinates), there was a better convergence during the trial 2. We deduced implicitly that there were some first trial rules which facilitated the convergence during trial 1 and that were transferred to trial 2. As an example, we saw in Figure 2.9 that the rule combining the behavior *right* with the pattern 1 knock was maintained during the trial 2.

### Cooperative Communication for the Task Achievement

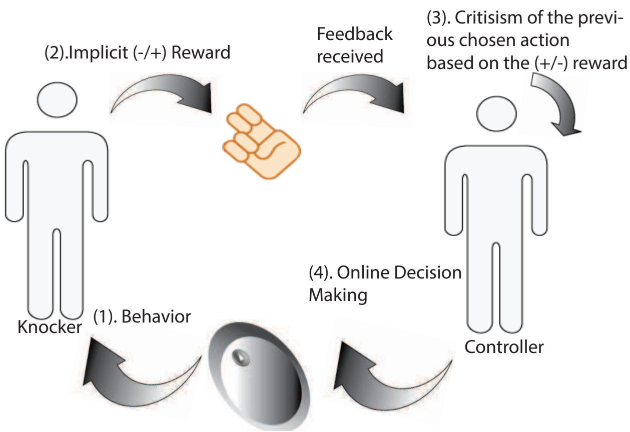



Fig. 2.11 Cooperative behavior between the controller and the knocker during the communication protocol formation.

By examining the data and Pearson correlation test values, we maintained that there was a significant correlation between the confusion states and the remedial knocking. On the one hand, this indicated that the controller was trying to maintain stable rules that he thought organizing the interaction. On the other hand, this indicated that the knocker cooperated with the controller in order to altogether shape a stable protocol of communication (Figure 2.11).

During the interaction, the controller tried to establish the communication rules by choosing the behavior that was previously more frequently (greedy policy[4]) associated with the received knocking pattern. He also auto-criticized his strategy based on his own assumptions and this was proved by the presence of some confusion states. He refined his assumptions according to the new rules that he imagined shared with the knocker. Finally, he chose a new behavior. His choice might lead to an agreement or a disagreement state. These insights led us to think about a model which integrated two components during the communication protocol formation, one related to the action choice and the other to the criticism of the executed action.

#### Performance Evaluation

Shared rules formation led to a significant decrease (as the t-tests and Figure 2.7 shows) of the task completion time during trial 2. We also noticed that there was a decrease in the convergence metric values during trial 2 (Figure 2.10). We deduced then that the pairs were growing closer to the stable communication protocol formation. This decrease was revealed by the elaboration of clear rules. As an example, pair 9 in Figure 2.9 succeeded on associating for the *forward* behavior 2 knocks during trial 2 after being confused during trial 1 between two patterns (2 knocks, 3 knocks). By applying the chi-square and Cramer's V (tables 2.1 and 2.2) tests, which evaluated the relationship between the knocking patterns and the controller's interpretations of these patterns, we found that the number of pairs showed a statistically significant relationship between the patterns, and that the behaviors increased from 7 out of 15 pairs (46.6%) to 11 out of 15 pairs (73.3%), indicating our scenario helped the users to acquire the meaning of the different emergent patterns and form communication protocols incrementally based on the previous interactions.

[4] It consists of choosing the most frequent behavior that was previously associated to the same number of knocks previously received and led to an agreement state; e.g.,: choosing the left behavior when we have 3 knocks led most probably to an agreement state while choosing back may have led to a disagreement because it has led less frequently used for an agreement state based on the previous interactions.

## 2.5 Modeling the Architecture of the Robot

### 2.5.1 Insights from the Human-Human Experiment

We seek to enable non-expert users to shape a communication protocol with a minimally designed robot. The fact that the robot used a novel minimal communication channel caused some confusion for the human. It required adaptation from him in order to understand how to provide the most convenient input for the robot while guaranteeing the intended output. In this vein, we noticed that people aggregated a small number of redundant patterns (such as 1 knock, 2 knocks, etc.) in order to guarantee a systematized output (e.g.: 1 knock for the left direction, 3 knocks for the back direction, etc.). For each instance of interaction, the controller chose an action based on the received knocking while he tried to affect for the gathered pattern the most frequently successful action that was tested previously. Afterward, the knocker would judge the controller's choice. If the chosen action did not converge with the knocker's desired direction, the knocker would compose another knocking pattern in 2 seconds (approximated value based on the KRT distribution) indicating that the controller's choice was incorrect. Since the controller tried to track the best combinations between the knocking and the robot's action, any new knocking that disrupted the execution of the newly chosen action (action interrupted before 2 seconds elapse) would lead to a disagreement with the controller's assumptions about the knocking pattern-action combinations. However, if no knocking was received the action is correct and consolidated the controller's assumptions about the knocking pattern- action combinations. We also found there were times that when the controller chose the action, he got confused and changed the action without being prompt by any knocking. This indicated that the controller chose the action but also criticized his choices. The knocker sometimes detected the controller's confusion which confirmed again that there were rules shared between both parties. The knocker then tried to cooperate by composing the same previous knocking pattern, indicating that the controller (or the robot here since the knocker did not know that a controller wizarded the robot) had to return to the other recently executed action.

In parallel to our insights, Reinforcement Learning (RL) is " learning through a *trial-and-error process* how to *associate states* to *actions* in order to maximize a numerical *reward*. The learner has to discover which actions yield the most rewarding state using the *greedy policy* and finally reach a meaningful state-action combinations" [63]. Therefore, if we suppose that:

- Command-like patterns referred to the states in the RL while we had different states such as 1 knock state, 2 knocks state, etc.

- The different robot's behaviors were the actions for the RL (4 actions: right, left, back, forward).
- The controller's choice that consisted of choosing the most frequently used action previously tested corresponded to the greedy action chosen based on the greedy policy.
- The presence of knocking after the robot started the execution of the chosen action and before 2 seconds elapsed is the negative reward.
- The absence of knocking (for 2 seconds) after the robot started the execution of the chosen action was the positive reward.
- The fact that the interaction went through agreement and disagreement states indicated that the adaptation corresponded to a sequential trial-and-error process just like in the RL.
- Both parties established different combinations of (knocking pattern - controller's interpretations) corresponded to the (state - action) cartography that emerged during a RL process.

We may deduce then that RL algorithms fitted to our problematic adequately. In addition, the decision making should be in a *real time*[5] because we obtained different communication protocols for the different pairs, indicating that any hand-programming of a possibly supposed same protocol adopted by all the pairs would fail. We should therefore reduce the scope of useful RL algorithms to only the online RL algorithms. Finally, and based on the first experiment's insights, we found that the controllers at times were auto-criticizing their strategies. This made us think about the actor-critic as an online RL algorithm that fitted to our problematic. An actor-critic algorithm integrates a critic and an actor. The critic uses a temporal difference learning (TD) to criticize the action that has been chosen, and the actor is updated based on the information provided by the critic [64]. Incrementally, the actor chooses the greedy action while the critic observes the relevance of the actor's choice after receiving the feedback. The relevance of an executed action is materialized in our case, by the presence (negative reward) or the absence (positive reward) of the knocking and leads to an agreement or a disagreement state. The proposed actor-critic model should lead to similar performance (decrease in the disagreement states, the task completion time and the

[5]Real time: Because the communication patterns emerge in a sequential fashion and we remarked that communication protocols were personalized to the pairs, any attempt to integrate a batch learning method to the robot's architecture could not succeed in establishing the same customized protocols that we had seen in the first experiment, and that it is why we needed an online machine learning method. An online machine learning method gathers the data and learns incrementally

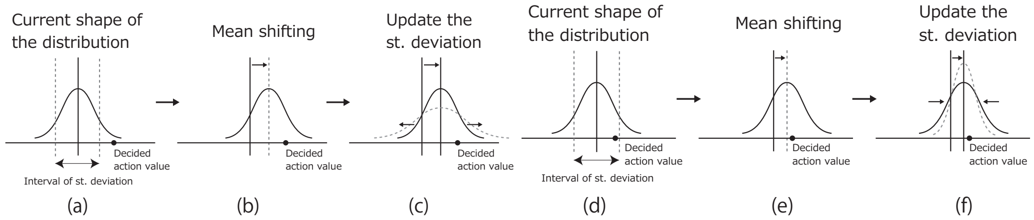



Fig. 2.12 Figure shows the re-adjustment procedure of state parameters; (1) the decided action value is outside of the standard deviation interval (Figure [a,b,c]); (a) current shape of the state distribution and decided action value, (b) mean shifting has started, and (c) the state parameters are updated and a new shape of the distribution is established; (2) Re-adjustment procedure of state parameters when the decided action value is inside of the standard deviation interval (Figure [d,e,f]):(d) the current shape of the state distribution and decided action value, (e) indication the shifting has started, and (f) the state parameters are updated and a new shape of the distribution is established.

convergence metric values) as in the H-H experiment. It should also guarantee transfer learning of the shared rules during trial 2 (while some combinations knocking-action of the first trial's communication protocol should be used during trial 2) so that stable communication protocols emerge.

## 2.5.2 Actor-Critic Algorithm:

**Actor Learning:**

Each knocking pattern (state) has its own distribution. $X(s_t) \approx N(\mu_{X(s_t)}, \sigma_{X_{(s_t)}})$ where $X(s_t)$ is defined as the number of knocks, $\mu_{X(s_t)}$ and $\sigma_{X_{(s_t)}}$ are the mean value and the variance while $\Pi(s_t)$ is the corresponding probabilistic policy associated to $X(s_t)$. We also assigned a distribution for the continuous-knocking pattern[6] that also helps in learning what behavior should be chosen once a continuous knocking is received by the robot. Initially, the action is chosen according to the probabilistic policy $\Pi(s_t)$. The state of the interaction changes to the state $s_{t+1}$ according to the user's knocking presence (disagreement)/absence (agreement). If the human interrupts the robot's behavior execution before 2 seconds [7] by composing a new knocking pattern, we have a disagreement state about the previous pattern's meaning (which was received from about 2 seconds). Consequently, the action that is chosen based on the probabilistic distribution in an attempt of exploiting the emerged knowledge failed. The actor updates the probabilistic policy $\Pi(s_t)_{nbknocks}$ and chooses the action henceforth

[6] We suppose that a knocking pattern that involves a number of knocks superior than 4 knocks
[7] We calculated approximately the value based on a pilot study

(until we meet an agreement state as a closure for the current pattern meaning's decoding process) by a pure exploration based on the equation

$$A(s_t) = \mu_{X(s_t)} + \sigma_{X_{(s_t)}} \sqrt{-2log(rnd_1)} Sin(2\Pi rnd_2) \tag{2.1}$$

where *rnd1* and *rnd2* are random equations that are designed to bring the values of the action between 0 and 3.

**Critic Learning:**

After each action selection, the critic evaluates the new state to determine whether things has gone better or worse than expected. The action is evaluated based on the presence or absence of knocking (positive or negative reward). This evaluation process is called the temporal difference (TD) error. The critic calculates the TD error ($\delta_t$) as the reinforcement signal for the critic and the actor where

$$\delta_t = r_t + \gamma V(s_{t+1}) - V(s_t) \tag{2.2}$$

with $\gamma$ is the discount rate and $0 \leq \gamma \leq 1$. According to the TD error, the critic updates the state value function $V(s_t)$ based on the equation:

$$V(s_t) = V(s_t) + \alpha * \delta_t \tag{2.3}$$

where $0 \leq \alpha \leq 1$ is the learning rate. A positive TD error indicates that the tendency to select $a_t$ when receiving the *i-th* current pattern should be strengthened for the future. A negative TD error indicates that the tendency to use that action with the gathered current pattern should be weakened, and in our case we weaken the possibility to choose the action $a_t$ for the *i-th* current received pattern. As long as the current pattern meaning's decoding is not achieved (exploration phase), (exploration phase), the critic will each time it encounters a disagreement state updates $\delta_t$, $V(s_t)$ and the distribution $N(\mu_{X(s_t)}, \sigma_{X_{(s_t)}})$:

$$\mu_{X(s_t)} = \frac{\mu_{X(s_t)} + A(s_t)}{2} \tag{2.4}$$

$$\sigma_{X(s_t)} = \frac{\sigma_{X(s_t)} + |A(s_t) - \mu_{X(s_t)}|}{2} \tag{2.5}$$

The modification during the update process helps to readjust the shared rules according to the previous interactions and assigns the most frequently correct behavior for the *i-th* current pattern received.

The idea here is to attempt to obtain the correct action inside the interval that represents the possible actions which should be executed when gathering the *i-th* pattern. The chosen behavior can be inside (when the action is chosen based on the probabilistic policy) or outside of the distribution (when the previously chosen action fails). If the behavior was outside of the distribution of the pattern, this means that the human has changed the rule concerning the *i-th* pattern. We operate in this case the mean shifting and the variance enlarging to recuperate the value inside the distribution (Figure 2.12(c)). As the decided action value is already inside the standard deviation interval and the TD was positive (Figure 2.12(d)), then our approach attempts to shift the mean value (Figure 2.12(e)) toward the action value while minimizing the standard deviation (Figure 2.12(f)). Shifting occurs when TD is positive by choosing the correct behavior as a part or the center of the distribution. In fact, if the action was outside the distribution then we assume that we are not sure that it is the new sustained rule (we only know that it was correct for one time) so we recuperate it inside. If that same action was combined with the same knocking pattern to which it was previously associated (*i-th* pattern), it becomes the mean because the robot is more certain it is the new rule of the *i-th* pattern.

## 2.6 Experiment 2: Human-Robot Interaction

Through this experiment, we tried to validate the robot's implemented architecture and verify whether the human and the robot can establish stable communication protocol.

### 2.6.1 Experimental Protocol

Each time we had a new participant, the instructor told him that he had to lead the robot to different checkpoints marked on the table before reaching the final goal point using knocking (Figure 2.4). We had two different configurations for the two trials of the experiment 2. We asked the participants to describe their experience when they finished the task.

In the first trial (Figure 2.4(left)), we expected the knocker to cooperate with the robot to invent his own protocol of communication by focusing on the most successful patterns that led mostly to agreement states just like in the first experiment. Meanwhile, we expected that the robot would focus on the rules' acquisition. The robot has to keep on guessing the most possibly correct behavior that must be combined with the right knocking pattern. It has also to refresh it assumptions in real time so that a stable communication protocol could be finally established. In the second trial, we assumed that the communication would

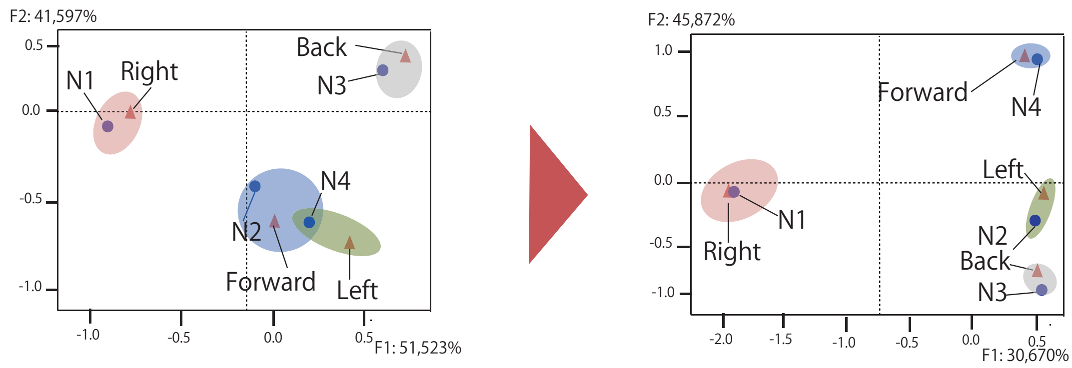



Fig. 2.13 Correspondence analysis for both trials for the participant 3 (Left: first trial, Right: second trial) in the first experiment where Ni represents the knocking patterns, e.g. : N2 represents 2 knocks.

become smoother as in the second trial of the first experiment. In this experiment, we had 10 participants (6 male, 4 female) ranging in age from 20 to 24 years old.

### 2.6.2 Results

After the experiment was finished, we tried to analyze the interaction scenarios in order to verify whether a communication protocol was established between the knockers' knocking patterns and the chosen actions.

We analyzed the video data by annotating with a video annotation tool called ELAN. Two coders, one of the authors and one other volunteer analyzed the behavioral data using the same coding rules for the first and the second trials. We calculated the average of Cohen's kappa from six arbitrarily selected videos in order to investigate the reliability. As a result, we confirmed that there was a reliability with $\kappa = 0.819$.

#### Evaluation of the Command-Like and the Continuous-Knocking Patterns based on the Videos

Based on the coded data, we counted the number of continuous-knocking pattern and the number of command-like pattern for all the participants and for the two trials to see whether participants had tendencies to use the command-like mode just like in the experiment 1. We discovered the participants were mainly using the command-like patterns with percentages (trial 1 : 91.14% of the patterns were command-like) and (trial 2 : 95.46% of the patterns were command-like). We conducted 2 t-tests to verify whether there was a significant difference between the 2 patterns usage: trial 1: *(t=4.596, d.f=9, p-value<0.01)*, and trial 2: *(t=7.486, d.f=9, p-value<0.01)*. As a result, we found a significant effect for usage of the command-like patterns during both trials, while a new state in the interaction cycle corresponded most of the time to a command-like pattern just as in the first experiment.

Participants confirmed also the fact that they need to use the simple command-like mode while one of the participants said: " ...I tried to knock slowly, to focus on the most useful knocking that will lead the robot to execute the right direction...", another one said:"...It is clear that I have to pay attention to the knocking and then I tried to affect 1, 2 knocks, etc. to facilitate remembering of the most convenient knocks...."'

### Communication Protocol Analysis

For a matter of illustration, we had chosen to depict the associations between knocking patterns and robot's chosen behaviors of the participant 3 based on 2 dimensions for the trial 1:(F1=51.523% - F2=41.597% ) and trial 2:(F1=45.872% - F2=30.670%)[8], just as in the first experiment (Figure 2.13). Based on the (Figure 2.13(right)), we maintained that *right* behavior was materialized by 1 knock, *forward* and represented by 2 and 4 knocks, *left* by 4 knocks and *back* by 3 knocks. In the second trial (Figure 2.13(left)), the protocol is slightly ameliorated where we can see a clear categorization of *forward* that is represented by only 4 knocks, while *left* is represented by 2 knocks, *right* is always represented by 1 knock, and *back* by 3 knocks.

### Adaptation Evaluation based on the Agreement and Disagreement States Comparison

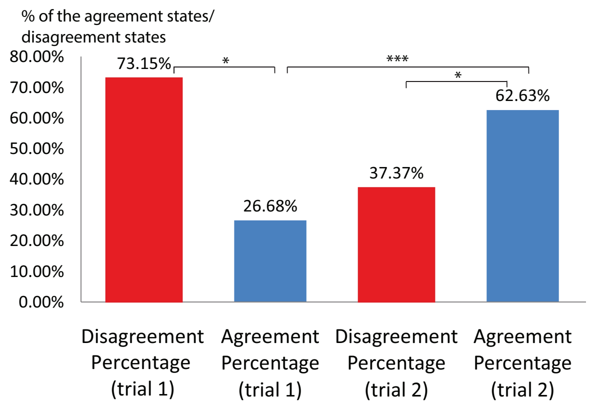



Fig. 2.14 The agreement and disagreement percentage during trials 1 and 2 (experiment 2).

[8]Here we had actually 3 dimensions for each of the trials F1, F2 and F3 to reach 100%, but the highest possible representation in 2 dimensions consisted of choosing the F1 and F2 more so than either F1 and F3 or F2 and F3

We counted the number of agreements and disagreements during trials 1 and 2 and for all the participants. A t-test showed that there were significant differences between the number of agreements and the number of disagreements usage during the trial 1 with a value: $t = 2.37$, $d.f = 9$, $p\text{-value} = 0.028 < 0.05$. We displayed the percentage of the first trial's agreements and disagreements in the Figure 2.14, where in blue we have the percentage of the agreements and in red we have the disagreements during the trial 1 and 2[9]. Based on the Figure 2.14, we noticed also that the number of disagreement states (73.15%) was higher than the number of agreement states (26.68%) during the first trial. A t-test showed that there were statistically significant differences between the number of agreements and disagreements during the trial 1 with a value $t=2.37$, $d.f=9$, $p\text{-value}=0.028<0.05$.

Based on Figure 2.14, we also noticed that the number of agreements exceeded the number of disagreements with a percentage value respectively 62.63% and 37.37% during the trial 2. A t-test between the agreement and disagreement states during trial 2 showed that this excess was statistically significant with (t-test:$t=2.108$, $d.f=9$, $p\text{-value} =0.049<0.05$). Finally, by calculating the t-test between the number of agreements of the first trial and the second trial, we obtained the above value ($t=5.359$, $d.f=9$, $p\text{-value}<0.01$). We can therefore conclude then that even though the second trial involved a configuration with new checkpoints, there were a higher number of agreements during trial 2. This implies that a transfer of learning occurred and facilitated the formation of a communication protocol during the trial 2 just like in the second trial of the first experiment.

**Comparison of the Task Completion Time of the Trial 1 and 2**

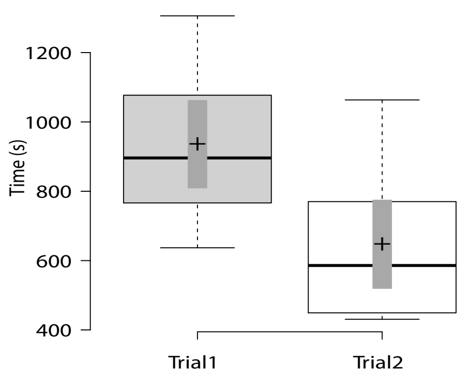



Fig. 2.15 Task completion time distributions during trial 1 and 2 (experiment 2)

[9]The percentages were calculated based on the same formula used during the experiment 1

The distribution of the task completion time datasets during the trial 1 (first boxplot in grey) and 2 (second white boxplot) were represented in Figure 2.15. Figure 2.15 shows that there was a decrease in the task completion time during trial 2. We applied a two-tailed t-test to verify whether there were statistically significant differences between the task completion time of the first and second trial. The results were significant with t-test value:(*t=2.959, d.f=9, p-value= 0.008<0.01*).

### Performance Evaluation based on the Convergence Metric Values

We wanted to explore whether there was a statistically significant difference between the system's performance during trials 1 and 2. For this purpose and based on the correspondence analysis results, we calculated the Euclidean distance between each of the robot's behaviors (red triangles as presented in the Figure 2.13) and the different patterns (blue circles as presented in the Figure 2.13). Thus, for each behavior we calculated the n possible Euclidean distances (assuming that we have n possible patterns). After that, we picked for each behavior the most minimal distance. We summed up the 4 most minimal distances and the resultant value afforded information about the most minimal distance that the pair knocker-controller achieved to form stable rules. We called this value the convergence metric which evaluated the system's performance. We repeated the same procedure for the 10 participants and for the two trials.

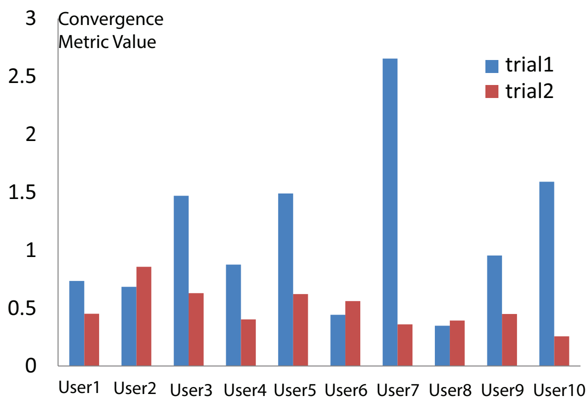



Fig. 2.16 The convergence metric values during trials 1 and 2 (experiment 2).

As in the first experiment, we display the results of trials 1 and 2 convergence metric values, where the convergence metric values of the first trial are shown in blue and the convergence metric values of the second trial are shown in red (Figure 2.16). Figure 2.16 shows that 70% of the pairs (7 out of 10 pairs) succeeded in reducing the convergence metric

Table 2.3 The test of independence (chi-square) between the knocking patterns and behaviors, as well as the Cramer's V (CV) values of trial 1(experiment2)

| Users | *Chi-square* | *CV* |
|---|---|---|
| User1 | $\chi^2$=51.977, d.f=10, ***p-value<0.001 | 0.425 |
| User2 | $\chi^2$=9.747, d.f=10, p-value=0.463 | – |
| User3 | $\chi^2$=20.531, d.f=8, ***p-value=0.009 | 0.206 |
| User4 | $\chi^2$=8.613, d.f=6, p-value=0.197 | 0.4194 |
| User5 | $\chi^2$=12.727, d.f=6, **p-value=0.048 | 0.477 |
| User6 | $\chi^2$=13.847, d.f=6, **p-value=0.031 | 0.397 |
| User7 | $\chi^2$=73.605, d.f=10, ***p-value<0.001 | 0.511 |
| User8 | $\chi^2$=11.563, d.f=3, ***p-value=0.009 | 0.525 |
| User9 | $\chi^2$=28.119, d.f=8, ***p-value<0.001 | 0.404 |
| User10 | $\chi^2$=6.111, d.f=6, p-value=0.411 | – |

values during the second trial, which indicated the pairs where closer from the convergence to stable communication protocols formation during the trial 2.

We computed the t-test between the convergence metric values of the trial 1 and 2 to verify whether there were statistically significant differences. We found then significant differences with t-test result as follows (*t=2.776, d.f=9, p-value=0.012<0.05*), indicating that users attempts to converge to stable protocols were more significant during the trial 2.

**Communication Protocol Evaluation based on the Independence Test Results**

To statistically measure the dependency between the knocking patterns and the different robot's behaviors, we computed the test of independence (Chi-Square) between the knocking patterns and the different behaviors as well as the Cramer's V values. Table 2.3 and Table 2.4 exhibited the results of the first and second trials for the 10 participants. Based on the Table 2.3, 7 out of the 10 participants (70%) succeeded in establishing a communication protocol with a Cramer's V-values ranging from 0.206 to 0.525 and thus ranging from a moderate to very strong relationship. During trial 2 (Table 2.4), the number of pairs that succeeded in establishing a communication protocol was almost the same despite the new configuration (the point coordinates of the checkpoints have been changed) which required adaptation for the human and the robot. Cramer's V-Values ranged from 0.283 to 0.387, which meant the relationship between the behaviors and the knocking patterns was moderately strong.

Table 2.4 The test of independence (chi-square) between the knocking patterns and behaviors as well as the Cramer's V (CV) values of trial 2 (experiment2)

| Users | *Chi-square* | *CV* |
|---|---|---|
| User1 | $\chi^2$=14.772, d.f=10, p-value=0.141 | – |
| User2 | $\chi^2$=31.977, d.f=10, ***p-value<0.001 | 0.381 |
| User3 | $\chi^2$=22.419, d.f=6, **p-value=0.001 | 0.387 |
| User4 | $\chi^2$=14.625, d.f=6, **p-value=0.023 | 0.355 |
| User5 | $\chi^2$=26.883, d.f=8, ***p-value=0.001 | 0.291 |
| User6 | $\chi^2$=13.073, d.f=6, **p-value=0.042 | 0.291 |
| User7 | $\chi^2$=17.885, d.f=8, **p-value=0.022 | 0.283 |
| User8 | $\chi^2$=3.583, d.f=8, p-value=0.893 | – |
| User9 | $\chi^2$=10.044, d.f=10, p-value=0.437 | – |
| User10 | $\chi^2$=15.714, d.f=6, **p-value=0.015 | 0.304 |

### 2.6.3 Discussion

#### Command-Like and Continuous Knocking Usage Evaluation

We remarked that command-like was more frequently used in comparison to the continuous - knocking mode. We concluded that the command-like mode was chosen spontaneously so that the problem can be decomposed into static number of states without telling the participants that they needed to modulate their knocking just like in the first experiment.

#### Interaction's Evaluation based on the Agreement and Disagreement

Based on the Figure 2.14, we found that the percentage of disagreement states exceeded the percentage of agreement states during the trial 1 and that the percentage of the agreement states exceeded the percentage of the disagreement states during trial 2 as well just as in the first trial. The t-test between agreement and disagreement states was significant during the trial 1 and 2. This indicated that, even though the second trial evolved a new configuration (former checkpoints coordinates changed), the participants were able to achieve significantly more agreement states during the second trial. This paved the way to conclude that during the second trial the pairs did not start from scratch again to establish the communication protocol, although there were some previously shared practices which helped to facilitate the communication protocol formation (transfer learning) just like in the first experiment.

#### Performance Evaluation

The rules sharing led to the significant decrease of the task completion time (Figure 2.15) with a significant t-test between the task completion time of the trial 1 and 2 where p-

Table 2.5 A comparison between the first and second experiments in terms of states of aggregation and performance

| | H-H Exp, T1 | HRI Exp T1 | H-H Exp, T2 | HRI Exp T2 |
|---|---|---|---|---|
| %State: CL-CK | 90.26 - 9.73 | 91.14 - 8.85 | 89.47 - 10.52 | 95.46 - 4.53 |
| %Agrmt-% Disagrmt | 38.08 - 61.91 | 26.68 - 73.15 | 64.97 - 35.02 | 62.63 - 37.7 |
| % users with stable protocols | 40 | 70 | 73 | 70 |

value=0.008<0.01. We also remarked that the interaction led to better performance during trial 2 (Figure 2.16). The t-test showed that there were significant differences between the trial 1 and trial 2 convergence metric values. These results indicated that the participants were growing closer to the stable communication protocol formation. By applying the chi-square and Cramer's V tests, which evaluated the relationship between the patterns and the behaviors, we found out that the number of pairs showed a statistically significant relationship between the patterns and the behaviors did not decrease. This indicated that gradually there was a strong relationship between the knocking patterns and the robot's chosen behaviors.

## 2.7 Summary of the H-H and the HRI Experiments Results

We may conclude based on the previous results of the HRI experiment that most of the participants succeeded in establishing personalized communication protocols. In the table 2.5, we attempted to compare the human-human experiment (H-H Exp) and the human-robot experiment (HRI Exp) results, while CL and CK correspond respectively to command-like and continuous-knocking patterns. Based on the table 2.5, we can see that the number of disagreements of the experiment 2 and during the two trials 1 and 2 (trial 1: 73.15% - trial 2: 37.7%), exceeded the number of disagreements of the experiment 1 (trial 1: 61.91% - trial 2: 35.02%). We may explain this by the absence of an implemented strategy in the robot that can decode the continuous - knocking patterns which occurred less during the HRI experiment and dropped during the trial 2 (trial 1: 8.85%, trial 2: 4.53% ) vs. a higher value during the H-H experiment which increased during trial 2 (trial 1: 9.73%, trial 2: 10.52%). This increase during the H-H experiment can be explained by the fact that the controller could detect the hazardous continuous-knocking patterns and decode them, while the knockers detected in the first trial that the continuous-knocking was handled by the wizarded robot. If we compare the percentage of participants that reached a convergence metric value under 0.25 during experiments 1 and 2, we found that only 40% of participants finally reached 0.25 as a convergence metric value vs. 90% of participants who finally reached 0.25 as a convergence metric value during the HRI highlighting. Even though we did not implement a strategy that handled the continuous-knocking patterns that emerge during the interaction, we still had better results in terms of convergence to stable protocols formation. We may explain this by the fact the participants during the HRI might had detected that command-like was the best strategy to guarantee a systematized output and that continuous-knocking led to a hazardous output, so they adapted themselves and implicitly avoided that strategy.

## 2.8 Conclusion

In this first part, we presented a human-human WOZ experiment, an actor-critic architecture and an HRI experiment. The WOZ experiment aimed at tracking down the interaction between the knocker and the controller to identify the best practices that may lead to the mutual sharing of the communication rules and facilitated the tailoring of a flexible control model which can be integrated in a minimally designed robot. We extrapolated these emerging patterns and the pairs (knocker - controller) succeed by shaping their adaptive strategies. In a second step, we implemented the robot's control model. Finally, we conducted the HRI in order to validate our architecture. Our work afforded a methodology that helped bootstrapping how an adaptive model can be tailored and integrated in a minimally designed robot. However, we remarked that for some of the participants the rules previously established are forgotten in trial 2 and those participants were blaming the robot for their forgetfulness of the previously established communication protocol. That it is why, in our next study we will try to find out a method that can help us mitigating the communication protocol reuse and maintain the communication protocol on a long term basis.

# Chapter 3

# Gracefully Mitigating Communication Protocol Reuse Breakdowns

## 3.1 Introduction

The drive for consistency when interacting with a robot can promote learned helplessness [65]. In fact, altered predicting error signaling while reusing interaction rules that were previously established during past HRI instances between the human and the robot or what we call PECP may contribute to some of the hallmarks of learned helplessness. Specifically, the human may have high confidence about the interaction rules of the PECP that he remembers being established previously between him and the robot while he could have got confused. Because he cannot predict errors and cannot accurately retrieve the rules of the interaction's protocol previously established, possibilities of inconsistency during the HRI increase and the human may feel lost during post HRI instances (when the PECP is supposed to be reused) [66].

Such a scenario can even lead to worse consequences. According to the attribution theory, in order to maintain a positive self-image while performing a task, people tend to attribute failure outcomes to external factors, such as the robot's imperfection [67] [68]. They may feel better about their abilities by shifting the blame for unsuccessful attempts while attempting to recall the PECP from themselves to the robot [69]. One can think that the robot might tell the human through direct speech that he (the human) is the wrong party because he has forgotten the PECP. However, considerable research from HRI and politeness theory shows that people cannot readily accept that technology defeats them by showing rejection for the human's orders [70]. Showing rejection for the human's orders can be considered as a harm especially for self-esteem seekers [71] while a robot may not injure a human being or, through inaction, allow a human being to come to harm according to Isaac Asimov's famous three laws of robotics [72].

Furthermore, research from literature in HRI focuses on PECP recall boosting for only multi-modal expensive robots and no considerable research to the little of our knowledge was conducted in order to investigate the PECP recall challenge when a non-expert user has to remember the PECP previously established between him and a minimally designed robot[1]. In our current research, we are more interested in minimally designed robots that are affordable (cost) for non-expert people. Adding another dimension that it is minimal design paradigm is challenging because rejecting directly the non-expert user's requests may lead in addition to the previously elicited problems that may cause the human's social face harm [2], another problem for the case of minimally designed robots that it is "the adaptation gap". The adaptation gap is related to the differences between the functions of the robot that users expect before starting their interactions which are highly related to the robot's appearance, and the functions they perceive after their interactions. An adaptation gap resulting from the difference between the minimalistic robot appearance and its role as an authority that may dictate to the human how to interact when the human forgets the PECP, may lead to a decrease in the robot's likeability and perceived competence [75].

Given the centrality of these issues, we propose to use indirect non deliberative IUs as non-linguistic utterances combined with the minimally designed robot's visible behaviors rather than the direct rejecting speech of the non-expert's requests when the non-expert user cannot remember the PECP. We argue that once IUs are combined with the robot's visible behaviors, the communication protocol can be maintained. Many cartoon films use IUs rather than natural language as a means of communication where viewers will coordinate the cartoon character's behavior with the IU to understand the context, e.g: Pingu. Thus, we assume that IUs contribute on the context's understanding. By combining, the situation presented in the cartoon with the IU, the human may understand the complete meaning. Linking a visible situation with an auditory icon many times (information encoding phase) may increase the possibility that we remember that particular information (recall phase). This is related to Paivio's dual coding theory that is based primarily on combining visual information with an auditory icon that can be a nonverbal sound to facilitate the information recall in the future [76]. It has been proven that cued recall consisting of presenting the non verbal or pictorial format of the information encoded may lead to better recall results rather than free

[1]A minimal designed robot have small number of sensors and simplified in terms of anthropomorphic features. The design of the robot should be efficient enough to make the minimalistic robot sociable but also affordable (cost) for common non-expert users.

[2]Social face: It is the individual's portrayed identity in a particular situation [73]. It is highly related to self-esteem [74].

recall when it is the human's responsibility to retrieve the complete information without us presenting anything to him [77]. Thus, if we assume that the non-expert user combines the robot's different visible behaviors (pictorial format of the information) with the non verbal IUs (non verbal format of the information) during a first HRI's instance (encoding phase), we might have high recall of the PECP if the robot generates the non verbal format (cued recall) of the information before executing the robot's behavior in order to facilitate the recall of the PECP.
This work seeks to answer two research questions: How to increase the PECP recall in shorter time for the case of interaction between a non-expert user and a minimally designed robot? Can we improve the participants' perceptions of the minimally designed robot's performance once we apply our proposed solution (dual coded feedback)?

## 3.2 Related Work

Since the proposed study and its experimental evaluation is motivated by theories from Social Psychology, design concepts and studies from HRI, this section provides an overview on relevant theoretical foundations in human-human interaction and design concepts as well as other HRI related work.

### 3.2.1 Face Threatening Acts

While it is laborious to establish a completely error-free interaction in HRI design, the issue of how to make non-expert users aware of their errors is critical to the concept of user-centered design [78]. It seems obvious that during an HRI, a robot may disagree with a non-expert user making an error while trying to retrieve the PECP. But, when the robot disagrees with the human's decision, the human will be embarrassed and may exhibit a negative reaction. As a reminder, we call that situation when the robot disagrees with the human and shows a less supportive behavior for the human's social face, a face threatening act (FAT).
The concept of FATs was originally described by Geertz [79] and Goffmann [80]. They discuss numerous principles of politeness theory that should be integrated in a human's daily interaction in society including face supportive behaviors. A fundamental assumption of politeness theory is that all individuals are concerned with maintaining a good public image or what we call a "social face" [81].
In this context, the main idea that we want to highlight is that any solution that it is proposed

for the issue that we discussed should avoid threatening the non-expert user's social face [82].

### 3.2.2 Proposed Solutions to Deal with or Prevent Miscommunication in HRI

In this subsection, we expose different miscommunication resolution methods presented in the HRI that can be categorized into two types which are the implicit and explicit methods.

#### Explicit Method

Several studies successfully explored miscommunication arising from users giving instructions in real-time interaction with an artificial agent executing those instructions during the experiment [83] [84], and related error handling is integrated in spoken dialog systems [85]. Error handling through the usage of spoken speech may cause lexical or conceptual difficulties while the robot sometimes cannot cope with the complexity and vagueness of natural language [86]. Argumentation was another alluring solution for the HRI community [87]. Argumentation consists on deriving reasoning semantics by analyzing the supports and defeats [88]. For that purpose, the robot should query the human for more information that may help it get the whole picture during the HRI. That it is why, inquiry and information-seeking dialogues could be employed to resolve interaction errors due to miscommunication [89]. But, again we are putting at risk the HRI, because the non-expert user is not supposed to deal with a robot that may waste their time with argumentation as the user expects total obedience from the robot.
Other studies in HRI, go beyond Asimov's laws of robotics and find that it is possible to reject a human's request while using some directives for that purpose [90]. We believe that the robot has to avoid negative frame speech including rejecting the human's requests which may in turn threaten the user's social face. People have a tendency to treat others much as others have treated them so in case the robot rejects the human, according to the law of reciprocity, humans will sooner or later do the same [26].
By extending the line of our research we believe that a speech act during an HRI has to support the human's social face, and ought not to be used to increase a human's frustration through disagreeing with the human's propositions [91]. Consequently, we avoid to use an explicit method (e.g:speech act) to alert the human about their faulty interaction attempts. We prefer to use an implicit method that helps to support the human's social face and succeed with diffusing frustration.

**Implicit Recall Methods**

In order to avoid a situation when a human does not understand the feedback or forgets each instruction's objectives, a few studies use a LED light as an implicit feedback strategy such as Naoki O. et al [92] where the LED light is used to remind silent bystanders to talk during a multiparty conversation. Thus, a miscommunication because of a user's speech prevailing during an interaction can be avoided. Knox W.B. et al [93] used red and green LED lights for TAMER the robot during a demonstration session in order to indirectly remind the user of the incorrect ways of using the pre-programmed robot. Some other studies use a pseudo-implicit method (forewarning) while an instructor explains how to use the robot before the interaction starts [44]. In [94], a whiteboard near Simon (the robot) is provided as a reminder about the concept representation and the types of sentences that the teacher could articulate.

First, we believe that, a LED light is an implicit communication channel but not sophisticated enough to inform the human about their error without accentuating the frustration (e.g: the red light indicating error increases the negative feelings). Besides, informing the human before the interaction starts just like in [44], may lead to the human's confusion about the instructions and feeling that the interaction is not quite natural. Moreover, a forewarning is not useful when the amount of instructions organizing the interaction increases. Finally, writing on the board ([94]) to remind the person of the concepts taught to the robot, is also inconvenient because it is not a natural communication channel as an important HRI community goal is to make the communication intuitive and natural.

Another work [95] straddles the line under the usage of hesitation gestures in collaborative tasks while transferring information indirectly to the human that a miscommunication is occurring during the HRI. That implicitly may cause a trust problem because a non-expert user may attribute the hesitation gestures as an indication of a robot that may make errors in the future [96].

Interfaces seem to be another solution that may help to avoid miscommunication while in [97], Pierre Rouanet et al considered using interfaces such as smartphones, wiimotes and lasers as a good means to avoid any miscommunication. We argue that these interfaces, allowing the non-expert user to understand, vary in the kind of feedback provided to the user which may lead to an increased cognitive workload in addition to the fact that it is unnatural communication method.

### 3.2.3 Child-Caregiver Interaction

To think broadly about the interaction between caregiver and infant is extremely important. First, this is the starting point in life where initial relationships are built. Second, the baby's limited ability to communicate is important to consider. Adults can communicate through facial expressions, actions; voice, language, text and symbols, and the baby will only use hummed sounds. Even though there are limited means of communication between the caregiver and the baby, they still can interact and reuse simple communication protocols that may orchestrate their daily interactions [98]. This, is undoubtedly of great significance and a valuable inspiration source helping to resolve the issues related to our study. Since people accept the use of hummed sounds or what we call IUs, are able to establish a communication protocol via IUs and remember it during future child-caregiver interactions, there is also a possibility that the same thing may occur when we use the IUs during the HRI.

### 3.2.4 Inarticulate Utterances (IUs)

We define IUs as sounds consisting of chirps, squeaks, hummed sounds etc. which are used as social cues during HRI. It is still possible to include many similarities between natural language and IUs. For example, general prosodic features from the human voice may be mapped to IUs in order to make them sound more natural or child-like [98] [99] [100] [101] since we are interested into reproducing similar interaction circumstances in the HRI that are present in the child-caregiver interaction. Our IUs consist of utterances designed to resemble natural language, but deliberately have no linguistic semantic content. A prominent example of this can be found in the robot Kismet [98], where IUs were used in place of natural language.

The standpoint that we take in this work is that IUs do not constitute a real language. Using the fundamental properties of a language as proposed by Hackett [102] as a reference, namely displacement, arbitrariness, semantics, discreteness and cultural transmission, we argue that IUs have the capacity to accommodate all of these. However, there are three vital elements missing: syntax, lexicon, and grammar.

We believe that IUs may be considered as a proto-language. IUs are non linguistic and are unable to communicate complex ideas (e.g. "go 5 meters to reach the location") when compared to natural language. This is why we urge caution in thinking about IUs in the sense of a pure language and we also believe that it will not cause social face threatening. In addition to that, it is an implicit natural communication channel since it is used by children in the child-caregiver interaction context and helps to maintain the communication protocol. Moreover, we argue that people readily attribute meaning to novel IUs as suggested by some

HRI studies [103] [104]. As meaning can be attributed to these IUs, combining them with robot's visible behaviors may lead to an increase in the communication protocol recall in future interaction instances if the robot presents the IU before executing the corresponding action (cued recall). Dual coding in this context, consists of combining the IU with the robot's visible behavior [105]. Finally, one may add that using IUs suits the minimally designed robot because it does not require expensive extra tools that have be integrated in a minimally designed robot.

## 3.3 ROBOMO Architecture

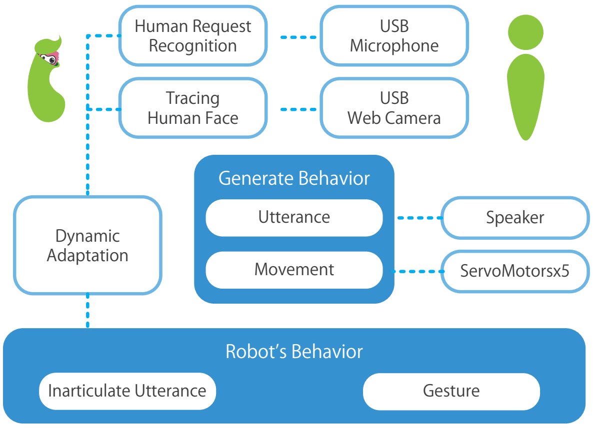



Fig. 3.1 The overall architecture of ROBOMO: The user's voice is captured using the microphone, the robot decodes the user's request using Julius (a software of Japanese language recognition). After that, the robot uses the speaker to generate the IU satisfying the user's request.

To communicate with ROBOMO, the user has to talk on the microphone so that, the robot can recognize using Julius[3] [106], the meaning of the user's request. ROBOMO tracks the user's face using a Web Camera whilst listening to the human because we believe that face tracking can increase a user's engagement (Figure 3.1). ROBOMO integrates a micro PC to adapt to the user's request and provides a verbal response through the speaker. ROBOMO uses five servo-motors (AX-12+) to exhibit different gestures such as 'bowing to the left, right, forward or back', 'a confirmation gesture', etc..
ROBOMO has a long shaped body utilizing an attractive container (made of plush material) and has no arms. We intentionally gave ROBOMO a pitcher plant (Nepenthe) appearance

[3] Julius is a continuous real-time speech recognition decoder for speech-related studies that does not require training.

to encourage people to interact with it, much as one might with a young child or a pet. Although used for personal navigation, our accompanying mobile robot is unable to walk.

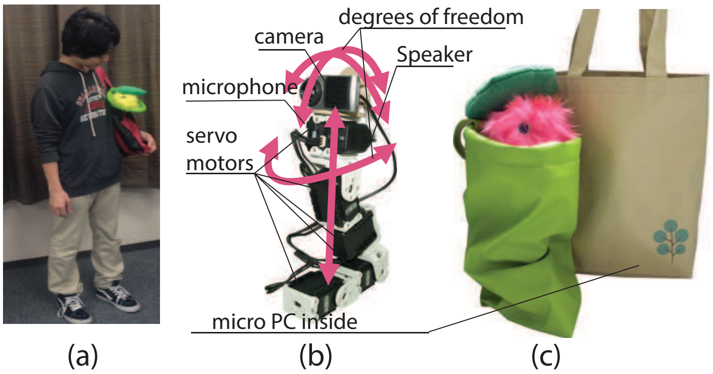



Fig. 3.2 (a) A picture of ROBOMO interacting with a user; (b) A close-up picture showing the inside of ROBOMO the robot; (c) The robot is made of plush material and may emerge from the bag whenever the human interacts with it.

## 3.4 Research Questions

The evaluation of the approach presented in the previous sections included one laboratory study that sought to demonstrate the feasibility of the proposed approach in enabling minimally designed robots to indicate indirectly to non-expert users erroneous instructions which are issued by the non-expert users and that do not comply with the communication protocol that was previously established in previous interaction instances.

More specifically, the study sought to answer the question, does combined IU (auditory information) with the minimally designed robot's visible behavior (visual information) enables the minimally designed robot to display appropriate social feedback to the human? Can it minimize changes in the communication protocol that was established in previous interaction instances? If we could validate these two research questions then this may help reducing the information retrieval time in the new interaction instances since the number of erroneous instructions would be reduced.

That it is why, another research question that we may draw is: does our approach facilitate the PECP recall in a shorter time? Also, does it increase the minimally designed robot's perceived likeability, competence and human's social face support?

## 3.5 Experimental Design and Conditions

To study the research questions above, the study followed a three-by-one, between-participants design. Participants were randomly assigned to one of the three conditions. The three experimental conditions included the following:
IUs condition: The minimally designed robot combined its behaviors with the IUs to facilitate the human's memorization and recall of the PECP (one IU per one robot's behavior; e.g: IU "A" is combined to the left behavior.).
Changed IUs during the recall phase condition (manipulated condition): The minimally designed robot combines IUs with behaviors just like in the Us condition. However, in the recall phase the IUs used during the encoding phase will be changed. This may help us to validate the importance of IUs usage and maintenance during both phases (encoding and recall) so that the dual-coded feedback could afford the expected communicative outcomes (better recall of the PECP and an amelioration of the non-expert user's perception of the robot's performance).
No IUs used (baseline): The minimally designed robot displayed only its visible behaviors while no IUs will be combined with its behavior.

## 3.6 Hypothesis

The study sought to test the central hypothesis that, by using IUs combined with the minimally designed robot's visible behavior, the minimally designed robot will enable the human to better memorize and recall the PECP in a shorter time which may produce positive outcomes on the objective and subjective levels while the minimally designed robot will be judged more competent, likeable, and supportive for the human's social face.
Paragraphs below outline specific instantiations of this central hypothesis.

### 3.6.1 Hypothesis 1.a

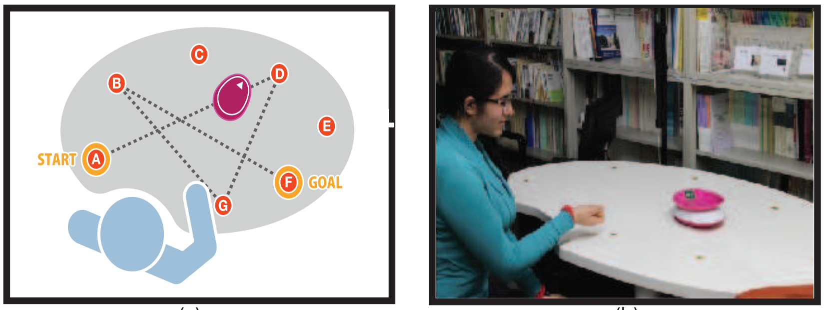
In a given task, IUs generated according to the IUs condition will elicit stronger communicative outcomes such as improved communication protocol recall and a shorter time required for the recall rather than the other two conditions.

### 3.6.2 Hypothesis 1.b

In a given task, IUs generated according to the IUs condition to hopefully activate the same effect of dual coding theory will improve the participants' perceptions of the minimally designed robot in measures such as likability, competence, and human's social face support more than the other two conditions.

## 3.7 Setup

### 3.7.1 Main Task in the Videos




(a) (b)

Fig. 3.3 (a): The experimental setup: The volunteer has to knock on the table so that the robot can translate the composed knocking and chooses an appropriate behavior; (b) a user interacting with SDT the robot.

We considered in our experiment two minimally designed robots called ROBOMO and SDT which we presented previously.
In all conditions, the minimally designed robots try to collaborate with the human in order to achieve a task. We designed these robots in order that they can be used as service minimally designed robots in the future.
Our experiment included two human-robot interaction scenarios:

- Visiting some checkpoints marked on the table with SDT the robot (first scenario: Figure 3.3).
- Collaborating with ROBOMO to find a location (second scenario: Figure 3.6).

**Task Related to SDT**

In the first scenario (Figure 3.3), the task consists of collaborating with a minimally designed robot that it is SDT to make the dish robot visit different checkpoints marked on the table.

In this context, a volunteer has to knock on the table (Figure 3.3) in order to make the robot visit the different checkpoints.

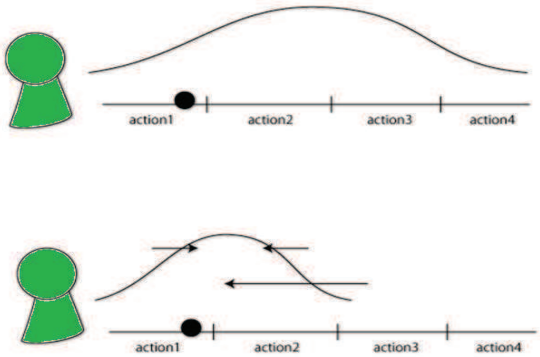



Fig. 3.4 As time goes by the distribution of each behavior is narrowed so that for each knocking pattern, only one action is associated.

Four microphones positioned under the table help to detect the sound and modulate the knocking in a way that the minimally designed robot can detect whether it is a rapid or a slow knocking and they also help to calculate the number of knocks. As an example, one can imagine a human knocking twice on the table very quickly. The knocking input in this case for the robot is 2 rapid knockings. The robot is capable of showing nine behaviors which are: "going forward", "going left", "going back", "going right", "stop", "vibration", "a whole turn from right to left", "a whole turn from left to right" and "denial" to refuse moving. Our minimally designed robot named SDT will try determine the right behavior to be executed from a composed knocking pattern.

The robot uses an algorithm that is an actor-critic which was generalized in comparison to the old version in order to include 9 behaviors rather than only four behaviors in our previous work [107]. In fact, the robot will affect for each knocking pattern a normal distribution that will finally converge in to a small set of possible behaviors. e,g: for the behavior "going right", the human will make 2 rapid knocks, the robot will learn that 2 rapid knocks means "going right", the numeral of the right behavior (each behavior has a numeral: e.g: 3) will be the mean of the normal distribution related to 2 rapid knockings. After some time the human changes his mind and affects the 2 rapid knockings to going left, in this case the normal distribution related to the 2 rapid knockings will be shifted so that it includes the numerals of the two actions (going right and left) (Figure 3.5). If an action is no more associated with the knocking pattern, the distribution will be updated as well in order that the action can be discarded (Figure 3.4).

As time goes by, the human will try to mirror only one robot's behavior to each knocking

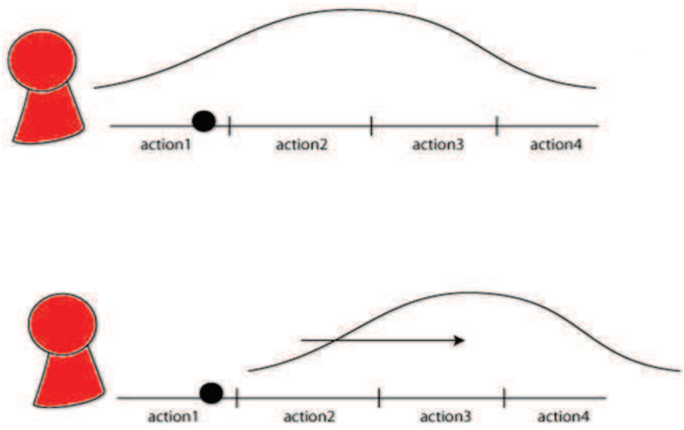



Fig. 3.5 As time goes by, each of the actions that are no longer required when a special knocking is composed will be discarded from the knocking pattern distribution.

pattern and that it is how a communication protocol is established while the rule in this context is in the form of "for x knocking, we have the robot's behavior y" [107].

**Task Related to ROBOMO**

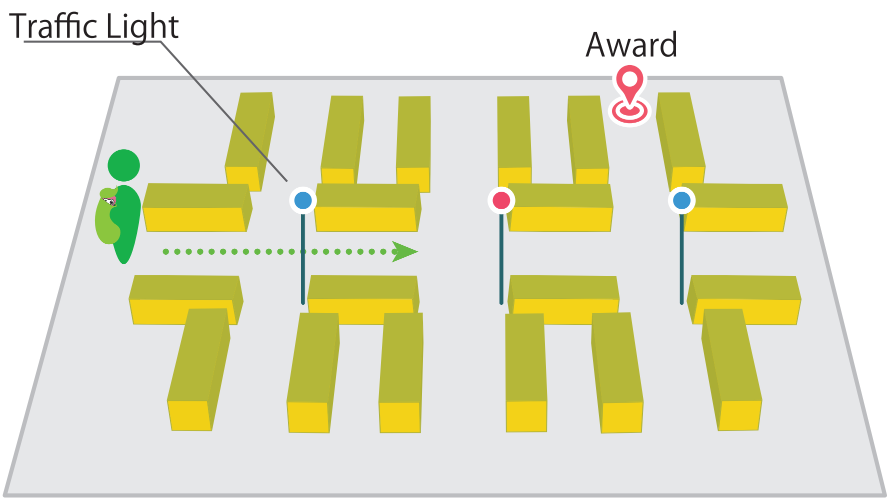



Fig. 3.6 The experimental setup: The volunteer has to hold the robot and ask ROBOMO about the correct direction to finally reach the hidden award.

In the second scenario (Figure 3.6), we setup an indoor space for a navigation task that contained intersections (Figure 3.6). A volunteer interacts with ROBOMO in order that he/she can find out the directions to visit a particular location. To pick the right behavior, the volunteer is instructed by the robot. While walking a volunteer, may stop sometimes and asks ROBOMO whenever he believes that he needs the robot's help by saying: "what

should I do?".
The volunteer can ask about directions or the traffic light colors in order to complete the task and reach the reward (music compilation in a DVD) location. The volunteer was instructed to ignore the reward location and to only rely on the robot's directions in order to reach it. We have chosen a typically complex configuration containing different checkpoints to increase the number of times when the volunteer has to ask the robot. The robot is capable of using a range of expressive body gestures in order for it to inform the volunteer about the right behavior that they can undertake. The robot's behaviors may express different contexts related to the volunteer's question: "go right", "go left", "go back", "go straight", "stop", "confirmation", "denial", "go", "slow down". Now, depending on the condition, each gesture can be associated with only one IU, multiple IUs, or no IUs. ROBOMO is controlled by a controller that may assign the right answer for each time the volunteer asks. He may also control the robot's gestures as well as the IUs remotely.

### 3.7.2 Procedure to Record the Videos: Two Scenarios

For each scenario, the volunteer's interaction was recorded in three different videos that elicit the 3 different conditions explained in paragraph 3.5.
In the conditions one and two, the robot used pre-recorded IUs, modulated in pitch to be gender-ambiguous and that are combined with the robots' visible behavior. For the case of SDT, the visible feedback consists of the robot's movement and body behavior such as vibration. For the case of ROBOMO, the visible feedback consists of the robot's body gestures.
After the videos of the volunteer interacting with the robot are recorded, we randomly assign participants to one of the videos.

### 3.7.3 Resulting Generated Videos

In the condition 1, the social-scientific specifications in the dual coding theory indicates that in general people remember better a behavior or a situation when it is combined with an auditory icon such as the IUs that we proposed. We call this video (since we have 2 scenarios; one related to SDT and another to ROBOMO) : Video1 Category.
In the condition 2, the IUs that the minimally designed robot used to combine with the behaviors changed during the recall phase. In fact, during the video recording each IU is combined with one of the robot's behaviors. We present the video for the participants so that they can have an idea about the CP. For the whole videos the goal was to verify whether participants remember the PECP or not by presenting (cued recall) or not (free recall) the

IUs. Specifically, the participants in condition 2 have to remember the PECP based on a cued recall. However, instead of presenting the same IUs used on the video during the recall phase, we change the range of IUs so that we can be sure that any remembrance of the PECP during condition 1 using the dual coded feedback is due to the usage of IUs: Video 2 Category.[4].

Finally, in the no IUs video, the interaction included no specific feedback but as a feedback afforded for the human, the human can only obtain the robot's visible movement. We call this video (since we have 2 scenarios): Video 3 Category.

## 3.8 Experimental Procedure

### 3.8.1 Participants

A total of 32 participants took part in the study. All participants were English speakers from the Toyohashi area with an average age of 22.07 years (SD=3.06), ranging from 18 and 43. Average familiarity with minimally designed robots among the participants was relatively low (M = 2.25, SD =1.7) and average familiarity with the experimental tasks was also low (M = 4.5, SD = 1.8) on a scale of one to seven. Participants were recruited through an email invitation via our JFS database and through personal contacts of the researcher. The majority of participants were students of the Toyohashi University of technology of Japan. Participants each received 1000 yen compensation for their effort.

### 3.8.2 Procedure

After signing the consent form, the participant is seated behind a desktop. During a baseline period of five minutes, participants filled a questionnaire about their current mood[5]. After that, a male experimenter greeted the participant and provided a brief introduction on the goals of the study. The participant watches the first video of the first scenario (five minutes), which is followed by a five-minute break while the experimenter prepares for the second scenario's video. The participant then watches the second scenario's video. After the second scenario finishes, the participant completes some questionnaires regarding likeability [108], social face support [109] and competence [110].After one week, the participant has to return to the laboratory to participate in a small quiz concerning the first scenario.

[4]This may help us to validate the importance of IUs usage and maintenance during both phases (encoding and recall) so that the dual-coded feedback could afford the expected communicative outcomes (better recall of the PECP and an amelioration of the non-expert user's perception of the robot's performance).

[5]*http://irtel.unimannheim.de/pxlab/demos/indexSAM.html*

If the presented video of scenario 1 was from the "Video 3 category", we ask the participant what rules were used to make the robot moves or does each of the different SDT's robot moves (scenario 1). A crucial variable that can be deduced is the number of correctly recalled rules. If the previous videos were Video 1 or 2 categories, then we present the IU to the participant and we ask them to identify the rules that were used to make the SDT execute each of the different moves. For Video category 1, we present the same IUs that are used during the first time (when the human watched the video). However, as for video 2 category, we changed the range of IUs by a new set of IUs that are different then those used previously (when the human watched the video related to condition 2) just as we explained in paragraph 3.7.3.

As for scenario 2 (ROBOMO task generated videos), we try to extract the reaction time (time needed to correctly exhibit ROBOMO's appropriate behavior combined with the volunteer's question) that is delimited by the end of the instructor's spoken phrase of whether there are some rules that the participant remembers and which were used in the video of ROBOMO and the end time during which the human is correctly imitating the robot's gesture that is related to the participant's evoked command. In this context, the participant has to evoke the activating command and the related behavior by imitating through a body gesture. Each time the participant finishes with imitating one rule, we ask them whether they think that there are more rules to be considered and we then start calculating the reaction time from the end of the instructor's question about whether there are extra rules or not and the end of correctly imitating the new behavior after evoking the command correctly.

If the scenario 2 video is from category of videos 1 or 2, the instructor asks whether there are some extra rules that ROBOMO has used, exposes a generated IU (that was used or not in the video: this depends of the condition) and then waits for the participant's answer. In this context, the reaction time is the period of time that it is delimited by the end of the IU generation and the end of imitating the robot's gesture correctly.

After finishing, the participant was debriefed, thanked and received 1000 yen for his participation.

### 3.8.3 Measurement and Analysis

The two independent variables in the study were the IUs manipulation (no IUS (condition 3) vs dual coded feedback (condition 1) vs manipulated condition (condition 2)) that the robot used and participant gender. The dependent variables included objective measures of task performance such as communication protocol rules recall (for scenario 1: SDT) and the time needed to recall the rules (for scenario 2: ROBOMO) as well as some subjective measures related to the participants' perceptions of the robot (likeability, competence, social face support).

**Objective Measures**

The first measure considered the participant's recall of the communication protocol rules. This measure included a total of nine questions, all related to the rules of the communication protocol established in the first scenario. The questions follow a multi-select format where for each knocking pattern (SDT) a behavior should be combined.
The second measure is related to the time it took the participants to finish imitating the robot's gesture correctly after evoking the corresponding command correctly. Specifically, this measurement captured how quickly the participants finished eliciting the correct rules relating to: (1) the directions (right, left, back, forward), (2) traffic lights (go, stop, slow down)(3) the confirmation (yes)/the denial (no).

**Subjective Measures**

The post-experiment questionnaire included scales to measure the participants' perceptions of the robot in dimensions of competence of behavior (seven items; Cronbach's alpha= 0.78), social face support (14 items; Cronbach's alpha = 0.89), and likeability (5 items; Cronbach's alpha = 0.83). The participants rated all questionnaire items using seven-point rating scales.

### 3.8.4 Conditions Checks

To test whether the manipulation in the IUs condition was successful, the post-experiment questionnaire included a number of items on whether they combined the robot's behavior with the IUs (a matching could be established), and whether the robot's proposed IUs are always the same when combined with the robot's behaviors and if they noticed some variation in the combinations of (robot's behaviors, IUs)[6].

### 3.8.5 Analysis Methods

The analysis of data followed one-way analysis of variance (ANOVA), while the analysis of data on objective and subjective measures involved a two-way ANOVA, including participant gender as a second factor to control for gender differences. These tests included Omnibus tests to identify the general effects of experimental manipulation on dependent variables and contrast tests that compared the IUs condition against the baseline condition

[6]This is related to the manipulated condition

and the manipulated condition for hypothesis testing. All contrast tests used the Scheffe method for adjusting significance levels in multiple comparisons.

## 3.9 Results

### 3.9.1 Conditions Checks

The analysis of data from condition checks showed that the participants were able to identify the differences across the different videos. The experimental manipulation of the IUs had a significant effect on whether they thought that the behavior which the robot executes and combines with the IUs matched, F(2,26) = 9.58, p <0.001, $\eta_p^2$ = 0.42, and whether they found the robot's proposed IUs are always the same when combined with the robot's behaviors or if there is a variation., F(2,26) = 6.42, p=0.006, $\eta_p^2$ = 0.33.

### 3.9.2 Hypothesis 1.a: Correctly recalled rules

As a reminder Hypothesis 1. can be elicited as follows: In a given task, IUs generated according to the IUs condition will elicit stronger communicative outcomes such as improved communication protocol recall rather than the other two conditions.

#### Hypothesis 1.a: Number of Correctly Recalled Rules

The data from the information recall measure provided support for this prediction. The number of correct answers out of ten questions in the recall test were on average (mean=4.74 sd,= 1.38), (mean=4.37, sd=1.95), and (mean=7.37, sd=2.66) for the no IUs condition (video3 category), manipulated condition (video 2 category), and condition 1 (video 1 category), respectively.
The ANOVA found a significant main effect of the robot's IUs stability (using the same IUs during the encoding phase) on recall accuracy, F(2,26)=7.18, p =0.003, $\eta_p^2$ = 0.35.
Contrast tests showed that recall performance was significantly higher in the condition 1 (video 1 category) usage than in the manipulated condition (video 2 category), F(1,26) = 13.71, p = 0.001, $\eta_p^2$ = 0.34, or than in the No IUs used (video 3 category), F(1,26)=7.87, p=0.009, $\eta_p^2$ = 0.23. Figure 3.7 illustrates these results.

#### Hypothesis 1.a: Time needed to correctly recall the previously established rules

Hypothesis 1.a also predicted that there is a reduced time needed to remember the rules, in the condition 1 (video 1 category) in comparison to the other conditions (videos 2 and 3

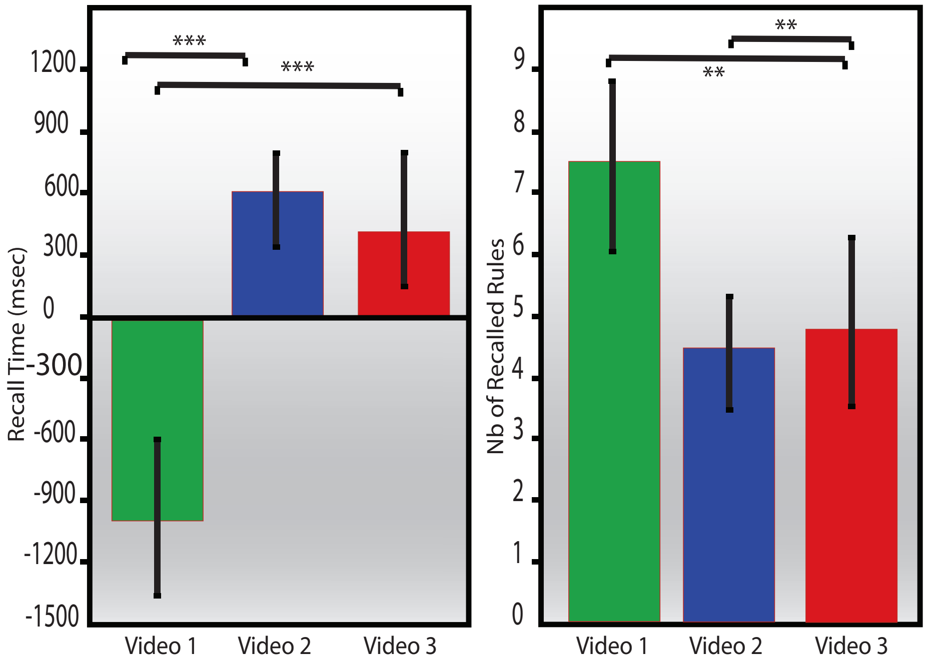



Fig. 3.7 Results on rules correctly recalled and reaction time to retrieve the learned rules watched on the videos. (±), (*), (**), and (***) denote p <0.10, p <0.05, p <0.01, and p <0.001, respectively.

categories).

The analysis of data from this measure partly supported the hypothesis; when the end of the robot's inarticulate utterances (in the case of video 1 or 2 categories) or the instructor's end of spoken question (in the case of video 3 category) was set to zero, the average times in milliseconds that the participants took to remember the corresponding robot's behavior were (mean=457.03, sd= 292.43), (mean=582.14, sd= 612.71), and (mean=-975.22, sd = 405.4) for the No IUs (video 3 category), Highly variated IUs (video2 category), and constant (only one IU per one behavior to facilitate the recall) IUs conditions (video 3 category), respectively. The ANOVA found the main effect of the experimental manipulation on the time measure, $F(2,26) = 28.1$, $p < 0.001$, $\eta_p^2 = 0.61$. Contrast tests showed that participants in the IUs (video 1) condition located objects in significantly shorter time than participants in the highly variated IUs (video 2) condition, $F(1,26) = 52.4$, $p < 0.001$, $\eta_p^2 = 0.61$, and No IUs condition (video 3), $F(1,26) = 33.2$, $p < 0.001$, $\eta_p^2$=0.55, did (Figure 3.7).

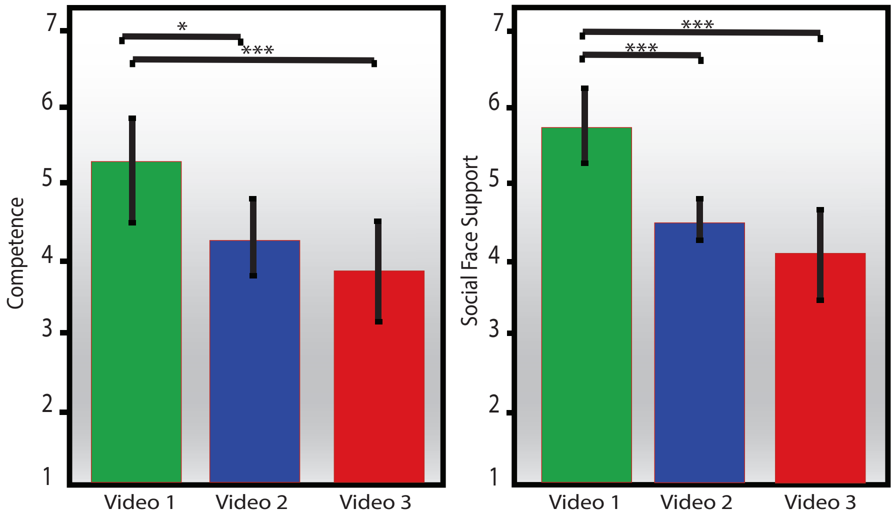



Fig. 3.8 Results on the human's perceptions about the robot in terms of competence, likeability and social face support. (±), (*), (**), and (***) denote p <0.10, p <0.05, p <0.01, and p <0.001, respectively.

### 3.9.3 Hypothesis 1.b: The participant's perception of the robot

Hypothesis 1.b predicted that the participants would perceive the robot to be more likable, more competent in behavior, and more human social face supportive in the IUs condition than they would in the other conditions. The data from subjective measures provided partial support for this hypothesis. The analysis showed the main effect of the experimental manipulation on participants' perceptions of the robot's competence, $F(2,26) = 4.33$, $p = 0.024$, $\eta_p^2 = 0.250$, and human's social face support, $F(2,26) = 12.67$, $p < 0.001$, $\eta_p^2 = 0.49$, but not on it likability, $F(2,26)=2.25$, $p=0.125$, $\eta_p^2=0.11$.

In particular, participants in the IUs condition (video 1) rated the robot to be more competent than they did in condition 2(video 2), $F(1,26) = 5.31$, $p = 0.03$, $\eta_p^2 = 0.17$, and No IUs condition (video 3), $F(1,26) = 7.97$, $p = 0.009$, $\eta_p^2 = 0.24$. Similarly, the participants in the IUs condition (video 1) rated the robot to be more human social face supportive than they did in the condition 2 (video 2), $F(1,26) = 15.84$, $p < 0.001$, $\eta_p^2 = 0.38$, and No IUs condition (video 3), $F(1,26) = 23.14$, $p < 0.001$, $\eta_p^2 = 0.47$. Contrast tests with the data from the likability measure showed that participants rated the robot as marginally more likable in the IUs condition (video 1) than they did in the condition 2 (video 2), $F(1,26) = 3.95$, $p = 0.05$, $\eta_p^2 = 0.13$, and the No IUs condition (video 3), $F(1,26) = 3.09$, $p = 0.091$, $\eta_p^2 = 0.106$. Figure 3.8 also illustrates these results.

## 3.10 Discussion

The results provided support for Hypothesis 1.a in measures of information recall. The use of IUs enabled the robot to elicit improved recall of the PECP rules that were presented in the videos.

A close look at the participants' behaviors in the no IUs condition (video 3 category) and the condition 2 with the second scenario illustrates why the robot's behaviors in these conditions elicited inferior task outcomes. In fact, the data showed that the participants needed 400-600 milliseconds to recall the rule while barely in condition 1 when the robot starts the IU , the human remembered the activating command and the related behavior before even that the robot finished the IU.

The results also supported Hypothesis 1.b in measures of the robot's perceived competence, social face support, and partially in the likability measure. The ability to facilitate the communication protocol encoding based on the IUs usage enabled the robot to elicit improved perceptions of the robot in dimensions of competence and the human's social face support, while resulting in marginal improvements in the robot's likeability.

A potential explanation for the lack of significant improvements in the likeability measure is that, while competence and social face support are key qualities for a robot providing a service to a human (like in the case of our robots that it are trained to be used in a restaurant or in the street and as the instructor told to the participants), the participants might not have found likeability to be particularly relevant to the social situations in which they interacted with and evaluated the robot. In fact, as we debriefed the participants to get an idea about their opinions concerning the robot's new design, we remarked that 72% of the participants ascribed positive traits to the robots in condition 1. However, they indicated that robots that need to afford a service for a user, should be more friendly enough to be socially accepted by people. Participants afforded many propositions to make the robots more friendly such as adding more degrees of freedom related to the robot's movement, adding an IU related to laughing and mourning, etc. None of the comments indicated that the proposed IUs are not likeable. That it is why, an alternative explanation is that, given the marginal effects in the predicted direction, the study lacked sufficient statistical power to show significant differences due to the small sample size.

## 3.11 Conclusion

This study presented a novel approach that may help in the future to enable minimally designed robots to indicate to humans without threatening their social faces that the PECP is about to change. This approach helps on doing so without evocation of whether the human is the faulty party or not and without that the robot takes the responsibility of reconstructing again the communication protocol in the new interaction instance because that may decrease the robot's likeability and lead the human to use the robot as a scapegoat rather than focusing on their own errors while reusing the PECPs. In our work, we tried to study the feasibility of using a different kind of feedback that consists of combining what it is seen when the robot is displaying a behavior (can be considered as a mental image) and what it is heard (auditory icon: IU) in order that the human indirectly retains in his memory the communication protocol in an easy and indirect way.

We tried to compare three conditions: baseline condition that consists of the robot exhibiting only it visible behavior (no IUs are used), manipulated condition that consists of changing the IUs during the recall phase (video 2 category) and the IUs condition (video 1 category). We measured the differences between the three conditions in terms of rules recall and time needed for rules retrieval. Results indicated that using simple IUs where for each robot's visible behavior, we have one IU that it is combined, ameliorates the human's remembrance of the previously encoded (established) rules in previous interaction instances in a shorter time. We also remarked that changing IUs during the recall phase leads to worse interaction outcomes in terms of recall and the robot's subjective evaluation in comparison to the IUs condition (when the IUs are maintained the same during the recall phase).

In our next experiment, we will try to verify whether this study's insights could be applied for the case of a real HRI. Another issue that we need to take care of in the next study is to propose a technique that helps people to not get bored while listening to the same IUs. In fact, some of the participants felt that the interaction is a bit boring. That it is why, in the next study, we will try to propose a variation-repeat technique that may help hopefully to decrease boredom and thus increase the user's impression about the robot's performance.

# Chapter 4

# How A Robot can Help Maintaining the Communication Protocol

## 4.1 Introduction

The use of robots in our daily life has long been a goal of robotists with a vision that alludes to robots being able to cooperate and communicate, but also learn from human partners. Several realms related to different disciplines such as machine learning [111], ecological psychology [112], etc. are actively working towards the goal of making a robot teachable. However, in order to efficiently learn from interactions with non-expert users, robots do not only need sophisticated machine learning algorithms, but also attention should be paid to the non-expert users way of teaching to the robots [78]. A good teacher should maintain an accurate mental model of the robot's state (e.g., what is understood so far, what rules of interaction (CP) have been established that can be considered as the basic blocks in order to construct more complex rules in the future, etc.) in order to increase the interaction's outcomes. The robot, in turn, helps the teacher by making its learning process transparent to him through expressive feedback. It should demonstrate its current knowledge and mastery of the task [113], [114]. Through this reciprocal and tightly coupled interaction, the teacher and the robot cooperate to simplify the task of CP construction and maintenance. However, this tradeoff is far from being easy to achieve as numerous challenges are encountered when we have a minimally designed robot and a non-expert user.

The minimal design concept was first proposed by Okada et al.[115]. Okada et al. [115] concludes that the robot's appearance should show minimal use of anthropomorphic features, so that humans do not overestimate or underestimate the robot's skills [8]. By minimal design, we mean eliminating non-essential components and keeping only the most fundamental functions. We expect that, in the future, minimally designed robots will be more affordable than other multi-modal robots [107]. People will use such minimally-designed robots for a variety of tasks and services. As an example, one can mention "cleaning the floor" with Roomba the robot [9]. Interacting with such minimally-designed robots may represent the first experience of a non-expert user interacting with a robot. This leads us to assume that non-expert users will possibly have high expectations about the robot's adaptive capabilities [116]. They expect that a robot should show an obvious obedience when the non-expert user assigns an instruction for it. As a result, in the case of minimally-designed robots, the probability of inconsistent feedback afforded by the non-expert user during the CP construction or reuse, can increase for multiple reasons.

First, the non-expert user may assign the same instruction each time in a different way while the robot should stick to what it learned previously. In such a case, the robot may adapt to the new instruction. However, as long as the non-expert user could not see that they should adhere to the rules (CP) taught previously to the robot (PECP), they may blame the robot for being non adaptive. In such a case, the non-expert user will stop using the minimally designed robot. Second, forewarning a non-expert user about the fact that they should adhere to the CP taught to the robot may drive them to think that the HRI is not natural since in all cases they will have to handle a machine that cannot meet their expectations of adaptation, obedience and sociability. Finally, a non-expert user that tries to maintain such a reality (the robot cannot be perfect enough to deduce implicit rules like humans do) and who realizes that they forget the taught PECP, may use the robot as a scapegoat to avoid any responsibilities and stop using the robot.

In this vein, in order that the long-term use of minimally designed robots could be guaranteed, a main challenge that should be resolved here is the increase of PECP remembrance without putting significant burden on the non-expert user by expecting that he can memorize all of the taught rules (CP). In fact, through the reciprocal and tightly coupled interaction that we presented we have a weak node that is "having a good teacher" (since we address the problem of having a non-expert user). That it is why, the other node of the reciprocal interaction should be strengthened to maintain an equilibrium. Consequently, that it is how we arrive at the solution that the minimally designed robot should guide the non-expert user by making its learning process more transparent to him through a more expressive method of feedback.

We expect that the new expressive feedback that can be used by the minimally designed robot may reduce the cost of PECP modification because of the user's forgetfulness without reducing the robot's final, asymptotic performance. Even though a minimally designed robot cannot use multiple communication channels; which may lead the robot to become

costly, the feedback should be expressive enough to guarantee sociability, a decrease of PECP forgetfulness and a cheap cost.
One of the main theories of Paivio in the context of information recall is the dual coding theory. Paivio used the idea that forming mental images aids on recall [117]. According to Paivio, there are two methods one can expand on learned material: sound associations and visual imagery. Dual-coding theory postulates that both visual and sound information are used to represent the information [118] in the human mind. The mental codes corresponding to these representations are used to organize incoming information that can be stored, and retrieved for subsequent use. Both visual and sound codes can be used when recalling information [118] (cued recall[1]). Presenting images could be a burden for a minimally designed robot since we would have to add a screen in addition to the fact that it is not a natural way of communication that we use in daily life. Therefore, we decided then to focus on sound information. The main idea will consist of combining the robot's visible behavior and sound information (an IU) with the instruction that is taught to the robot. During the reuse, the robot has just to generate the sound information before executing the action to reduce the error rate and time wastage. We expect that such sound information (the IU) may refresh the user's memory and lead him to remember the correct instruction.
Previously, we designed a novel scenario where the non-expert can use only one communication channel which is knocking [107]. To communicate with our minimally designed robot SDT, the non-expert user has to knock on the table to express his intention of making the robot go left, right, backward or forward. The robot has to learn the meaning of the knocking, and choose an action that converges with the human's intention. We showed that, we can simulate the procedure that the human uses to make the robot incrementally establish a CP.
In our current study, the main point that we focus on consists of the fact that, in each SDT-robot interaction instance (trial), we remark that the non expert user-robot pair creates a new CP that is completely different from the PECP of the previous HRI instance because of the user's forgetfulness of the PECP. We want to investigate whether users can maintain the same CP if the robot combines visible behavior and sound information (an IU) with the taught instruction. During the reuse of the PECP, SDT has just to generate the sound information (IU) before executing the action to reduce the error rate and time wastage. We expect that this may hopefully refresh the user's memory and lead him to remember the correct instruction.

[1]It is a cued recall because the robot tries to help the human to remember the rules by presenting cues which are in a visual or sound format.

## 4.2 Related Work

Since the proposed study and its experimental evaluation is motivated by theories from Social Psychology, design concepts and studies from HRI, this section provides an overview on relevant theoretical foundations in human-human interaction and design concepts as well as HRI related work.

### 4.2.1 Proposed Solutions to Deal with or Prevent Miscommunication in HRI

In this subsection, we will expose different miscommunication resolution methods presented in the HRI that can be categorized into two types which are the implicit and explicit methods before explaining more about the inspirational motives behind our choice of IUs and the robot's visible behavior combination.

#### Explicit Methods

In our context that it is miscommunication occurring during the HRI, by explicit methods we mean deliberative messages. These messages afford direct conclusions to the humans in order to argue with them, reject their request or make a confusing proposition.
Several studies successfully explored miscommunication arising from users giving instructions to an artifact executing instructions [83] [84], as well as related error handling that is integrated in spoken dialog systems [119]. Error handling through the usage of spoken speech may cause lexical or conceptual difficulties and the robot sometimes cannot cope with the complexity and vagueness of natural language [86].
Argumentation was another solution proposed by the HRI community [87]. Argumentation consists in deriving reasoning semantics by analyzing the supports and defeats [88]. The robot should ask the human for more information that may help it get the whole picture during the HRI. That it is why, inquiry and information-seeking dialogues could be employed to resolve interaction errors due to miscommunication [89]. However in this case, we put at risk the HRI because the non-expert user is not supposed to deal with a robot that wastes his time with argumentation instead of executing actions.
Other studies in HRI, went beyond Asimov's laws of robotics and found that it is possible to reject a human's request. For that, some directives were suggested [90]. We believe that the robot has to avoid negative framed speech, including rejecting the human's requests, because it threatens the user's social face. A social face is related to the human's concern of maintaining a good public image [81]. Any act that goes against the maintaining of a good

public image is considered to be a face-threatening act [80]. So, if an explicit speech act goes against the maintaining of a good public image, it is considered to be a face-threatening act. People have a tendency to treat others much as others treat them. In a case where a robot rejects a human, according to the law of reciprocity, humans will sooner or later do the same [26].

By extending the line of our research we believe that a speech act during an HRI has to support the human's social face, but ought not to be used to increase human's frustration through disagreeing with the human's propositions [91]. Furthermore, another more challenging point is related to the robot's minimalistic design that makes it difficult to include a defeating speech rejecting, arguing or pointing out the human's errors. A minimalistic robot that does so may lead to an adaptation gap resulting from the difference between the minimalistic robot's appearance and its role as an authority that may dictate to the human how to interact [75]. It may lead to a decrease in the robot's likeability and perceived competence . Consequently, we avoid to use an explicit method. We prefer to use an implicit method that helps to support the human's social face and succeed on diffusing any frustration.

#### Implicit Methods

In our context that it is miscommunication occurring during the HRI, by implicit methods we mean non deliberative information that helps shaping indirect conclusions related to the human's behavior in order that they change their attitude and pay attention to the instructions that they afford to the robot. We believe that, implicit methods can be considered as overheard messages. Overhearing a message is more powerful than direct conclusions [120] in terms of attitude change. People are more persuaded by information that does not seem to be designed to influence them because they do not realize when the information is over there and they let down their guards. There were many studies in HRI that discussed implicit methods guiding implicitly the human to pay attention to his behavior [92] [93]

### 4.2.2 Inspirational Points

As we highlighted in the introduction, we need a more expressive method that may empower the interaction between a minimally designed robot and a non-expert user so that the user's forgetfulness of the PECP can be avoided. The proposed solution should respect the fact that the robot is minimally designed and be harmonious to its simple appearance so as to not lead to an adaptation gap. The suggested method should also operate on the robot's expressive feedback rather than relying on the non-expert user to focus like an expert teacher on the HRI process.

According to the presented HRI studies, an implicit method could be more powerful to indirectly shape a human's retrieval of the PECP because it is not face threatening in addition to the fact that it can be considered as overheard material that can remain in a non-expert user's memory since it affords no direct conclusions.

#### Child-Caregiver Interaction

Adults are capable of communicating through actions; voice, language and symbols. A child can only use hummed sounds. Even though, there are limited means of communication between a caregiver and a child, both parties still can interact and reuse PECP that may orchestrate their daily interactions [98]. This is undoubtedly of great significance and of value to be an inspiration source to resolve the issues related to our study. People accept the use of hummed sound or what we call IUs. They are able to establish a CP via IUs and remember the PECP during future child-caregiver interactions. That it is why there is also a possibility that the same thing may occur when we use the IUs during the HRI. As a result, inspired from the child-caregiver interaction, we expect that using IUs during the HRI can be considered by non-expert users as a natural way of communication. Also, we think that using IUs can lead easily to CP formation and PECP retrieval just as in the child-caregiver interaction.

#### Need for Cognition

Another reason that we believe may lead non-expert users to focus on IUs when there is a confusing situation is people's natural need for cognition that may drive them to explore hidden regularities. Need for cognition is "the tendency for an individual to engage in and enjoy effortful thinking." [121]. That it is why we expect that the presence of IUs combined with the robot's visible behaviors rather than presenting only the robot's visible behaviors, would lead to better results because we assume that people will enjoy putting effort on linking IUs with the robot's visible behaviors to discover the logical redundant dually coded[2] rules of the CP.

### 4.2.3 Inarticulate Utterances (IUs) as Expressive Feedback

We define IUs as short auditory icons consisting of hummed sounds etc. which are used as social cues during an HRI. IUs consist of utterances designed to resemble natural language, but have no linguistic semantic content [98].

[2]By dually coded rule, we mean the usage of the robot's visible behavior (a pictorial format of the situation)-IU combination that it corresponds to a specific robot's instruction.

IUs can be considered as an implicit natural communication channel since they are used by children in the child-caregiver interaction context and help to maintain the PECP. Moreover, we argue that people readily attribute meaning to novel IUs as suggested by some HRI studies [122][104]. As meaning can be attributed to these IUs, combining them with a robot's visible behaviors may lead to an increase in PECP recall in future interaction instances if the robot presents the IU before executing the corresponding action (cued recall). Dual coding in this context, consists of combining the IU with visible behavior [105]. Finally, we can add that using IUs suits the minimally designed robot because it does not require extra expensive tools for it to be integrated into a minimally designed robot.

### 4.2.4 Variation-Repeat Feedback

Whilst there is no single definition of diversification, there is a general recognition of diversification as good [123]. Diversification of the robot's output is desirable during a social interaction. It represents new events and changes generated by the robot via behavior-generating algorithms and which may arouse people's curiosity to discover yet unpredictable regularities in the robot's behavior. As there is no meaning-making without a certain degree of creative imagination, such a diversification always involves from a person's behalf during the meaning construction of the new evolved behaviors, an adaptation to the robot [124] and in addition to that, users will start to believe more that the robot is somehow a conscious agent [124]. Thus the perception of the robot by human users is always positive and may not decrease over time. In fact, the first studies on the temporal progress of user experience in households equipped with a robotic vacuum cleaner indicate an initial enthusiasm in human users. However, any enthusiasm may decrease over time due to habituation to the robot's feedback [125]. Interactive robots may even raise initial enthusiasm [126], but in some cases humans may be willing to explore the limits of robots, as observed in robotic applications developed to operate in public spaces, where even a bullying type of behavior was shown by human passers-by towards the robot, e.g. [127].

In fact, even if a person initially likes for example a simple message, they do not want to hear it too many times or message wear-out might occur. Message wear-out is a condition of inattention and possible irritation that occurs after a person encounters a specific message too many times [127]. They may remember letter by letter the message but may dislike the message or try to avoid hearing it over and over. One good way to prevent message wear-out is to use repetition with a variation-repeat of the same information, but in a varied way [128]. That it is why, in our current study, we intend to add a technique of variation-repeat so that the robot can propose different IUs per the robot's visible behavior. Thus, the human can avoid this state of IUs wear-out which may influence their perception of the robot even if the PECP could be retrieved because of the repetition.

## 4.3 Setup

The subsections below outline the robot's IUs generation method and variation-repeat IUs generation technique.

### 4.3.1 Hypothesis

Our study sought to test the central hypothesis that, by using IUs combined with the robot's visible behaviors, the robot will be capable of displaying better expressive feedback for the non-expert user leading to better interaction outcomes that literature, related to child-caregiver interaction (4.2.2), dual coding theory (explained more deeply in the introduction) and the human's need for cognition tendency (paragraph 4.2.2), predict. Therefore, compared to a baseline condition that is displaying the robot's visible behavior as the only feedback offered to the human, a feedback combining IUs with the robot's visible behaviors could enable the robot to exhibit feedback that more effectively elicits these outcomes. The hypothesis below outlines specific instantiations of this central hypothesis.

**Hypothesis 1**. In a given task consisting on reusing a PECP, using the minimally designed robot's visible behaviors as the only feedback afforded for the non-expert user by the minimally designed robot would lead to a poor PECP rules maintain and increase in the task completion time during a second interaction's instance in comparison to the first interaction's instance when the human had no pre-established rules of interaction with the minimally designed robot. In such a situation, the HRI mediocre process during the recall of the PECP leads to a poorer non-expert's perception of the minimally designed robot performance in terms of likeability, competence and social face support in comparison to a situation where a non-expert uses a minimally designed robot for the first time.

Our previous work [107] strongly supports the first hypothesisit has been shown that people succeed on creating CPs customized to the human-robot pair but also personalized to each HRI instance because people forget the PECPs. We chose to add hypothesis 1 to show through numerical results one case study of a real minimally designed robot encountering a problem of interaction with a non-expert user who forgets the PECP.

**Hypothesis 2**. IUs combined with the minimally designed robot's visible behaviors improve the PECP recall in shorter time and helps in finishing the task faster in comparison to a situation when only the robot's visible behavior (B) is the only feedback afforded by the minimally designed robot to the non-expert user. Also, it helps ameliorating the human's perception of the robot's performance in terms of competence, likeability and social face support.

This hypothesis is supported by different studies from social psychology and human-human interaction [98] [105] [121]. Studies in child-caregiver interaction suggest that using IUs is a natural way of communication to interact. It can be expressive enough for adults to adapt to it. Also, it helps teaching the child different concepts and tasks [98]. This, makes it alluring to think about integrating it in the HRI. Moreover, by offering IUs combined with the robot's visible behaviors, the rules of interaction will be dually coded, while for each rule, the corresponding instruction will be coded in a visual format (by remembering what was the robot's behavior when that instruction is afforded by the human to the robot) and in a sound format through the presence of IUs [105]. The human will not lack a need for exploring these dually coded rules since people have a tendency to search for cognition when a situation is a bit confusing. Furthermore, using IUs is a novel communication channel that may trigger their curiosity [121].

Keeping the same IUs across different HRI instances is one of the key points in the dually coded rules that empower the combination of IUs with the robot's visible behaviors usage in terms of PECP recall. If we suppose that in a specific setup, we will make in a first trial the robot use an ensemble of IUs "A" during the robot's teaching, or what we call the encoding phase, while each IU from the ensemble "A" is combined with one of the robot's behavior[3] and in trial 2 (a new HRI instance) we use a new ensemble of IUs "B" during the recall phase (when the human is supposed to recall the PECP), we may draw then the hypothesis 3 as follows.

**Hypothesis 3**. Using a new ensemble of IUs "B" during the recall phase may lead to a confusion while recalling the PECP. It can also cause a longer time for rule retrieval and a greater period of time will be needed to achieve the task during the recall phase (when the PECP is supposed to be reused) in comparison to a situation when we use the same ensemble of IUs "A" that was used during the encoding phase (trial 1). Using a new ensemble of IUs "B" leads to worse human perception of the robot's performance in terms of likeability, competence and social face support in comparison to the situation when we keep the same ensemble of IUs "A" that was used during the encoding phase.

The next hypothesis is derived from research that has shown how repeating the same message may lead to message wear-out. One good way to prevent message wear-out is to use

[3]The IU is a sound format that it is played before the robot starts executing the behavior. The sound is the first code and the displayed behavior (the executed one) is the second one, while the information that it is coded is the instruction that the non-expert user should afford for the robot to get a specific behavior executed by the robot.

repetition with variation-repeat the same information, but in a varied way [128]. So if we consider that the information that needs to be generated in a varied way using a variation-repeat technique is the IU, then one can draw the following hypothesis.
**Hypothesis 4**. IUs generated according to the variation-repeat proposed technique lead to the same interaction outcomes during the encoding phase just like in the case when we constantly combined the same IU with the same robots' behavior so that a robot's instruction could be remembered correctly by non-expert users. When using such a variation-repeat technique, we expect to have the same performance in terms of PECP remembrance, time needed for rules retrieval and period of time needed for task completion time in comparison to when we use the technique of maintaining an IU per one robot's visible behavior. Also, we expect that when the minimally designed robot uses a variation-repeat technique, we have higher ratings in the non-expert's perception of the minimally designed robot's performance in terms of likeability, competence and social face support in comparison to when the minimally designed robot uses the same IUs assigned to the robot's visible behaviors".

**Knocking Pattern Design Space**

In our previous work [107], we remarked that there are two types of patterns: continuous-knocking patterns and command-like patterns. Command-like patterns consist of combining each behavior with a different combination of knocks (e.g.,3 knocks for Forward).
Continuous-knocking was used when there was contiguous interruptions in the robot's behavior[4]. We counted the number of both types of patterns based on the coded data of our previous work for each participant and for the two trials. We noticed that there was significant usage of the command-like patterns.
Users in our previous work were debriefed. Participants confirmed through most of their answers that they wanted to simplify the input for the robot in a way that they attribute modulated knocking. As an example, one can attribute 3 knocks when he wants the robot to move forward and 2 knocks when he wants for example to make the robot move to the right direction (Figure 4.1), etc.

### 4.3.2 Dually Coded Feedback

An IU consists of a single tone and prosodic component without any articulation or phonemic. We used the architecture proposed by Okada et al [129] so that we can generate IUs. We used this system just so that we can ensure that IUs that are generated are suitable

[4]Continuous-knocking was related to the presence of contiguous disagreements about the shared rules.

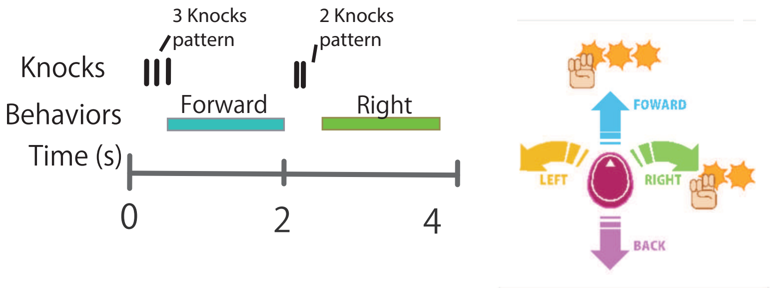



Fig. 4.1 A scenario showing an example of a short interaction between a user and SDT.

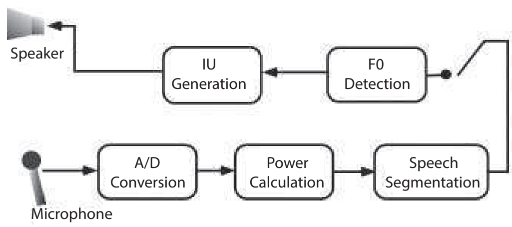



Fig. 4.2 Outline of the front-end modules used for capturing the speech and processing the signal to generate a sequence of frames comprising of the voice-only portions in the utterance: The goal of this processing is to translate the sound uttered by the user–which is received in the device as a series of amplitude samples from its microphone and Analog-to-Digital (A/D) converter–into a representation suited for the generation of a feature descriptor that corresponds to an inarticulate utterance.

for the robot's appearance [130]. The system works as follows (Figure 4.2): We asked a volunteer to read the utterances aloud. The volunteer's voice is captured and sampled at 16 kHz (A/D Conversion) (e.g: some of the utterances: go forward, go left, etc.). We call the result of the sampled recorded voice $x_i$. After that, the time sequence of the power pattern P(i) is calculated, e.g., the level of volume of the human voice, is calculated for each utterance (Power Calculation) $P_i$. The segmentation of each utterance is determined by the threshold energy based on the result of the power calculation (Utterance Segmentation). Then, the time sequence of an $F_0(i)$ pattern is computed ($F_0$ Pattern Detection). The $F_0$ patterns are experimentally detected by the average magnitude differential function algorithm [131]. The final IUs are synthesized by combining sine waves based on the power calculation and $F_0$ pattern (IU Generation). The following equation shows an example of synthesized wave $x'_i$.

$$phase(i) = 2 \times \Pi \times F0(i-1)/FS \tag{4.1}$$

$$amp(i) = P(i-1) \tag{4.2}$$

$$x'_i = amp(i) \times (sin(phase(i)) + sin(2 \times phase(i)) + sin(3 \times phase(i)). \quad (4.3)$$

where phase(i) is the value of the phase, amp(i) means the value of the amplitude and FS means the value of the sampling frequency. Each produced IU corresponds to an audio saved file that can later be called by SDT.

### 4.3.3 Variation-Repeat Dually Coded Feedback

The goal is to produce a variation-repeat IUs so that for each of the robot's behaviors, three IUs can be generated to indirectly code a knocking pattern that it is associated to the robot's behaviors. The robot has to generate when receiving a particular knocking pattern and before an action (right, left, backward, forward) is executed, one of the three IUs per one behavior (e.g; When receiving a two knock pattern, the robot had to generate IU "A", "B" or "C". When receiving a one knock pattern, the robot had to generate IU "D", "E" or "F" ), etc. So as a summary if the robot has to establish four rules on the form of "instruction - robot's behavior", with the VRDCF there will be twelve rules while for each one of the instructions, there will be three possibilities.

## 4.4 Study Performance

To explore the effectiveness of IUs as expressive feedback, that may resolve the problem of PECP forgetfulness if combined with the minimally designed robot's different visible behaviors, we used the workspace from our previous work to conduct a between-participants study of different setups and we drew different hypothesis to be validated.

### 4.4.1 Study Design

We included 3 different feedback methods the minimally designed robot may use to display feedback for the human:

- Baseline method (B): The robot uses its visible behavior, that is the robot's movement (moving to the right, left, forward or back), as the only feedback afforded to the human.

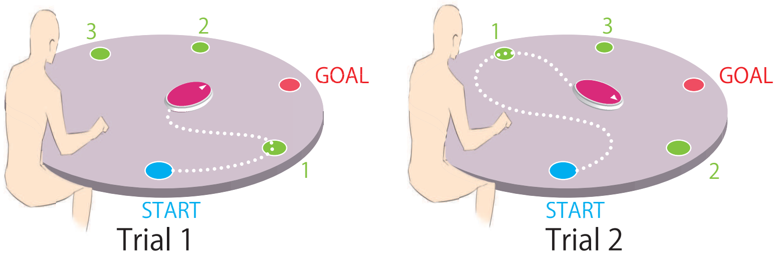



Fig. 4.3 In the first trial (left), the participant has to understand how the communication protocol is acquired in order to make the robot move into the designated locations on the table (start, 1, 2, 3, and goal) by means of knocking patterns. In the second trial (right), we change the sequence of the former points on the table, and then the user have to reuse the emerged rules of communication of the first trial to guide the robot into the newly defined locations.

- Dually coded feedback (DCF): The robot combines each of the instructions (knocking patterns) to two codes: a pictorial format through the situation pictured by the human (the robot's visible behavior) and a sound format through the usage of IU.
- Variation-repeat dually coded feedback (VRDCF): The robot combines each of the instructions (knocking patterns) to two codes: a constant pictorial format which consists of the situation pictured by the human (the robot's visible behavior) and a sound format that it is varied through the usage of different IUs. These IUs can be combined with the different robot visible behaviors in a way that many IUs could have been combined with only one pictorial format (only one robots' visible behavior; e.g: moving to the left). As we assume that humans have a natural tendency to explore regularities, we expect that they will track the sound codes (the IU) during the interaction that were attributed to each of the robot's behaviors and meanwhile people will not get bored because of a repeated same sound per behavior [5].

## 4.4.2 Task

Each time we conducted an instance of the experiment, we gathered a participant and an instructor to take care of him through exposing the different guidelines of the experiment.

[5]This feedback method was introduced to avoid the wear-out message problem, to keep the human constantly curious about the new proposed IUs that are combined with the different robot's visible behaviors and give the human the impression that the robot is a competent agent that knows how to diversify its output to increase the human's likeability and better support their social face needs.

The participant has to knock on the table in order to help the robot visit different points marked on the table (Figure 4.4). Before the participant enters the experimental room, the instructor told him the purpose of the experiment is to help the robot landing on different checkpoints marked on the table. The robot needed only to listen to the knocking, learn the meaning and then choose a convenient direction based on the gathered knowledge.
In the first trial, the participant had to cooperate in order to lead the robot to different sub-goals (Figure 4.3). In the second trial, we changed the coordinate sequence of the former points and the participant had to cooperate with the robot to reach the new coordinates sequence of the check points. Changing the coordinate sequence of the check points may guarantee that the participants were not accustomed to the configuration. Also, it helped us to confirm the participant used their adaptation abilities during the encoding phase (trial 1) and the PECP retrieval to succeed during the recall phase more specifically in the onset of trial 2. There are two trials, each lasting 10 minutes.[6]

Fig. 4.4 A participant interacting with the SDT.

### 4.4.3 Scenarios

As we explained in the paragraph 4.4.2, each participant will take part in two trials. In paragraph 4.4.2, we had not explained the feedback modality that the robot would use in these two trials. In fact, based on the three different feedback modalities explained in paragraph 4.4.1 we designed four different setups. For each setup, we assigned 20 participants that have to take part in the two trials. For each setup, the participant has to go through the same

[6]We estimated this period based on a previous pilot study.

task explained in paragraph 4.4.2. However, the only thing that differs from one setup to another is the robot's feedback modality.

- Setup 1: The robot uses (B) as a feedback modality for the two trials.
- Setup 2: The robot uses (DCF) as a feedback modality for the two trials.
- Setup 3: The robot uses (DCF) as a feedback modality for trial 1 while during the encoding phase each IU from the ensemble "A" of possible IUs (four IUs since we have four different robot's behaviors) is combined with one of the robot's behaviors (four behaviors). During the recall phase that corresponds to trial 2 (when the human is supposed to recall the PECP), the robot will use a new ensemble of IUs "B" combined with the robots' behaviors according to the same strategy that it is DCF rather than the ensemble "A" of the IUs that the human expects.
- Setup 4: The robot uses the (VRDCF) as a feedback modality during trial 1 (the encoding phase). In such case, for each of the robot's behaviors (four behaviors), the robot would have combined three different IUs to avoid the message wear-out phenomena that we discussed earlier in paragraph 4.2.4. So, for each of the four instructions (since we have four different robot's behaviors), the robot would have one pictorial code (the robot's visible behavior) and three different sound codes (three IUs). During trial 2 (recall phase) each time the robot received a knocking pattern (the instruction that is composed by the non-expert user), before that the pictorial code is displayed (the action is executed), the robot would present one of the three different IUs which are supposed to be combined with the same future behavior (in trial 1).

Obviously, the robot has to generate the sound format before that it executes the action so that the human remembers the correct rule and verifies whether the rule converges with their intention. This, may help reducing wrong steps and hopefully refreshes the human's memory to remember the different rules of the PECP (which instruction goes with which of the robots' behaviors; e.g: two knockings pattern is related to the robot going forward and by generating the IU(s) related to that behavior before it is executed by the robot, the human is capable of verifying whether the action that it is going to be executed is the one that they want, the robot does. In such a case, the IU(s) will help them to guess the action that it is going to be executed.).

### 4.4.4 Participants

We recruited 80 participants (47 males, 33 females) placing 20 individuals in each of the unique four different setups. Participants are from diverse majors and occupations. Ages ranged from 18 to 46 (M = 22.7, SD = 5.92). All the participants are from the Toyohashi University of Technology of Japan. They were recruited through email.

### 4.4.5 Procedure

Following informed consent, participants were seated in the experiment room. The experimenter explained the task to the participant, started the robot, and left the room. The participant then has to go through trial 1 as explained in paragraph 4.4.2. Before starting the interaction, one setup related to the robot's feedback modality is chosen randomly (e.g: setup one). Setups are chosen randomly but in a way that each setup would have been used by 20 participants at the end of the experiment. The interaction is video recorded. The participant has to finish trial 1 and then answers three questionnaires related to the robot's likeability, competence and social face support (paragraph 4.4.6).
After one week, the participant has to again visit the laboratory and cooperate with the robot so that it can visit the new sequence of the different checkpoints marked on the table (trial 2). The robot has to stick to the setup chosen previously. The interaction is video-recorded. Once the participant finishes, they again answer three questionnaires related to the robot's likeability, competence and social face support (paragraph 4.4.6). At the end of the study, the instructor debriefs the participant. The procedure took approximately 35 minutes. The participant is thanked and received 1000 yen for their participation.

### 4.4.6 Measures and Analysis

Our dependent variables reflected both objective and subjective outcomes.

#### Objective Measures

For each task, three objective measures described the effectiveness of the robot's feedback in helping the human to remember the PECP and achieve the task goal. These objective measures are the number of recalled rules, the time needed for the recall and the task completion time. All these variables can be determined by analyzing the recorded videos.

#### Subjective Measures

Often news is heard repeatedly because it is shown many times on TV. Does this help or hurt the material in the news? Recall that the mere exposure effect is the tendency for novel stimuli to be liked more after the individual has been exposed to it repeatedly. Accumulated research confirms that repeated exposure to information does influence memory [132].

More specifically, the initial attitude toward the information that is to be repeated makes a difference [133]. If the person has a neutral or positive response to the message initially, then repeated exposure can make the message more effective; if the person hates the message right off the bat, hearing it again and again will only make things worse. In an analogy to that, if we assume that the message in our case is the IU(s) then we need to verify whether by the end of each trial, the user has a neutral or positive response toward the robot. We measured the robot's perceived likeability and competence. Also, we assume that IUs do not construct a mere language, we think that we need to validate this assumption by measuring the user's social face support to verify whether the non-expert users were the victim or not of a face-threatening act when we used the (B), (DCF) and (VRDCF) in the different setups. Participant responses to questionnaires on seven-point rating scales measured the competence [110] (Cronbach's $\alpha$ = 0.73) to evaluate the robot's competence, the social face support[109] (Cronbach's $\alpha$ = 0.81) to verify whether the user's social face was supported during the HRI, and the robot's likeability [108] (Cronbach's $\alpha$ = 0.8). Additionally, participants were debriefed.

**Video Coding**

After the experiment finished, the interaction scenarios were analyzed in order that we identify the different established CPs. We analyzed the video data by annotating with a video annotation tool called ELAN. Two coders, one of the authors and one volunteer, analyzed the behavioral data captured in the video camera using the same coding rules for the first and the second trials. We calculated the average of Cohen's kappa to investigate the reliability. As a result, we confirmed that there was a reliability with $\kappa$ = 0.73.

There were simple rules that we used in the videos' coding. In fact, videos of trial 1 help determining the CPs (that correspond to PECPs for trial 2). To determine the final CP rules by the end of the interaction of trial 1, the coder has to track for each direction what was the corresponding instruction (knocking pattern); e.g: By the end of trial 1, the coder determined that two knocks were associated with the left behavior, three knocks with forward, one knock with the right behavior, four knocks were associated with the back behavior while a continuous knocking could express the user's request from the robot to stop. By the beginning of the interaction in trial 2, the coder has to determine what was the knocking that was correctly associated with the right behavior so that the PECP (the CP of trial 1) is preserved. Changed rules indicate that the user failed to recall the rules of the PECP.

**Analysis**

Data analysis involved paired t-tests for the first hypothesis and independent t-tests for the other hypothesis. G*power software was used to calculate the effect sizes.

## 4.5 Results

We discuss our results below. In each case, we cite the hypothesis that need to be tested as a reminder and then we expose the results. Competence, likeability and social face support are our subjective measures (three dependent variables). Number of recalled rules, time needed to recall and the task completion time are our objective measures (three dependent variables).

### 4.5.1 PECP Forgetfulness

Hypothesis 1 predicted that in a given task consisting on reusing a PECP, using the minimally designed robot's visible behaviors as the only feedback afforded for the non-expert user by the minimally designed robot would lead to a poor PECP rules maintain and would increase the task completion time during trial 2 in comparison to trial 1. In such a situation, the HRI mediocre process during the recall of the PECP leads to a poorer non-expert user's perception of the minimally designed robot performance in terms of likeability, competence and social face support in comparison to the situation when the non-expert used the minimally designed robot for the first time (comparison of trials 1 and 2 of setup 1).
We chose to add this hypothesis to show, through numerical results, one case study of a real minimally designed robot encountering a problem of interaction with a non-expert user who forgets the PECP.

**Objective Results**

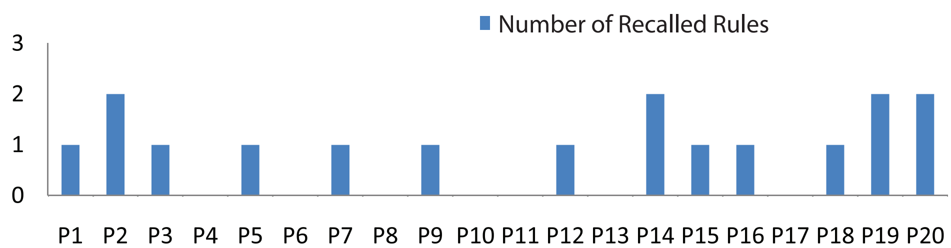



Fig. 4.5 The figure shows the number of recalled rules during trial 2 of setup 1.

Figure 4.5 shows the different 20 participants that used setup 1 and their corresponding number of recalled rules. As a reminder, setup 1 consists of using the method (B)[7] for both trials. Based on Figure 4.5, 35% of the participants forget completely the PECP established during trial 1, only 20% of the participants remember 50% of the PECP and no participant succeeded on remembering the whole PECP.
As, for the task completion time, we remarked that there is a main statistical difference between the task completion time in trials 1 and 2 with t-test= 2.872; p-value=0.009; d.f=19 and effect-size=0.642 (paired t-test between trial 1 and 2). Figure 4.6 shows the different subjective results as well as the task completion time of trials 1 and 2. Based on Figure 4.6, we notice that the task completion time decreased. This can be explained by the fact that some participants remembered some rules of the PECP. This reduced the time of interaction since such participants do not have to start constructing the CP all over again but they still remember some of the PECP's rules.

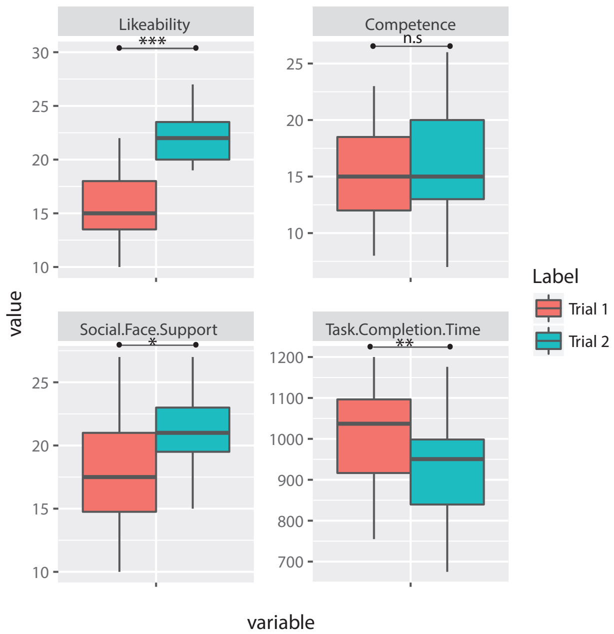



Fig. 4.6 The figure shows the subjective results as well as the task completion time corresponding to both trials of setup 1 (*:P-value<0.05, **:P-value<0.01, ***:P-value<0.001).

### Subjective Results

While the analysis did not find the main effect of using the robot's visible behaviors (B) on a human's perceived competence of the robot, there were significant statistical differences

[7] The minimally designed robot's visible behaviors are the only feedback afforded for the human.

between trials 1 and 2 in terms of likeability (t-test=6.18; p-value= $< 0.001$; d.f=19; effect size= 1.38) and social face support (t-test=2.66; p-value=0.015; d.f=19; effet size=0.60) (for both measures, we applied paired t-tests between trials 1 and 2). These results indicate that, although not all participants remember the rules previously established in trial 1, they still assign higher values (Figure 4.6) in trial 2 for both measures: likeability and social face support.
We may explain so by the fact that participants found it reassuring to discover that the robot still remember some of the rules of the PECP. However, they still think that the minimally designed robot is not competent enough because it does not correctly choose the right behaviors. Based on the participants debrief, participants were supporting this insight. One of the participants confirm:"Do I seriously have to teach the robot each time what it has forgotten?". Another participant during the debrief said:"I suppose that the robot has to be partly reprogrammed each time I need to use it. It acts like a baby: initially it will make some errors but I can see that it has learned something since the last time which is appeasing but not enough."

### 4.5.2 DCF to Maintain the PECP

Hypothesis 2 predicted that IUs combined with the minimally designed robot's visible behaviors (DCF) improve the PECP recall in shorter time and helps finishing the task faster in comparison to the situation when only the robot's visible behavior (B) is the only feedback afforded by the minimally designed robot to the non-expert user. Also, it helps to ameliorate the human's perception of the robot's performance in terms of competence, likeability and social face support.

#### Objective Results

By comparing the objective measures in trials 2, we remarked that there is statistically significant differences between trials 2 of both setups 1 and 2 in terms of the number of recalled rules (t-test=7.55; p-value$< 0.001$; d.f=38; effect size=1.44), time needed for the recall (t-test=4.57; p-value$< 0.001$; d.f=38; U-test=23; p-value$< 0.001$; effect size=2.31) and the task completion time (t-test=5.58; p-value$< 0.001$; d.f=38; effect size=1.76)
Figure 4.7 shows the first part of the objective results corresponding to trials 2 (number of recalled rules and the time needed for recall) of both setups 1 and 2. Figure 4.8 shows the subjective results and the second part of objective results (task completion time) of trials 2 corresponding to both setups 1 and 2 (trial 2 of setup 1 and trial 2 of setup 2). Based on figures 4.7 4.8, we notice that trial 2 of setup 2 gives higher results in terms of the number

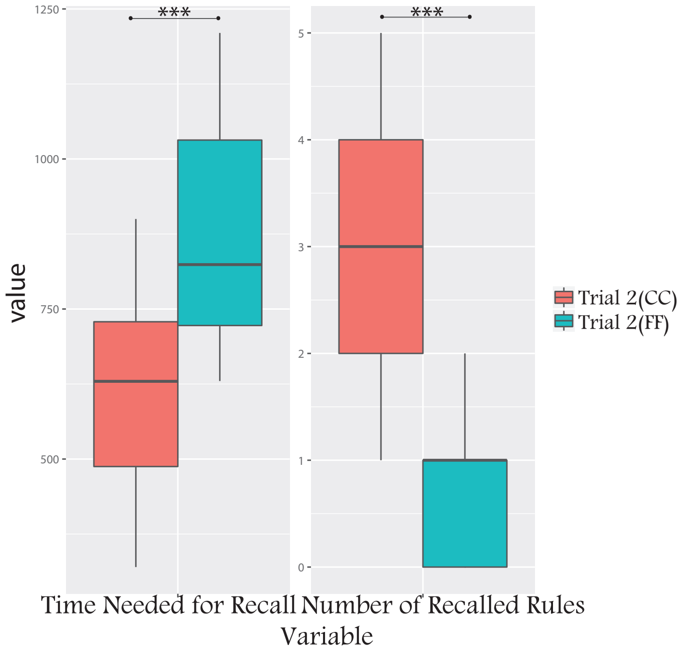



Fig. 4.7 The figure shows the first part of trials 2 objective results (number of recalled rules and the time needed for recall) corresponding to both setups 1 and 2 (*:P-value<0.05, **:P-value<0.01, ***:P-value<0.001).

of recalled rules and lower results in terms of the time needed for the recall and task completion time in comparison to trial 2 of setup 1.
These results converge with our hypothesis 2. DCF (setup 2) helps to increase the recall of the PECP in shorter time which lead to shorter task completion time in comparison to a condition when the minimally designed robot uses its visible behaviors as the only feedback afforded to the non-expert user (setup 1 with condition B).

### Subjective Results

By comparing trials 2 subjective measures of both setups 1 and 2, we remarked that there are statistically significant differences between trials 2 of both setups 1 and 2 in terms of competence (t-test=9.84; p-value=0.006; d.f=38; effect size=3.11), likeability (t-test=3.95; p-value=0.003; d.f=38; effect size=1.25) and social face support (t-test=9.39; p-value< 0.001; d.f=38; effect size=2.97)
Based on figures 4.7 4.8, we notice that trial 2 of setup 2 gives about higher results in terms of competence, likeability and social face support in comparison to trial 2 of setup 1. These results support our hypothesis 2. The usage of IUs combined with the minimally

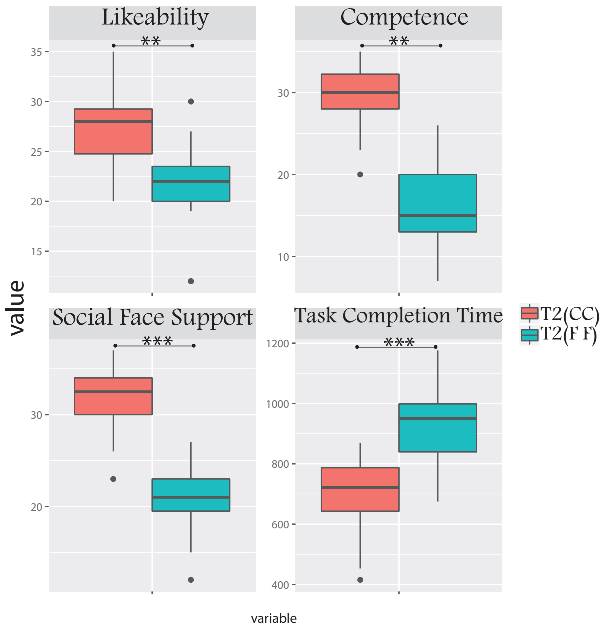



Fig. 4.8 The figure shows the subjective results as well as the second part of trials 2 objective results (task completion time) corresponding to both setups 1 and 2 (*:P-value<0.05, **:P-value<0.01, ***:P-value<0.001).

designed robot's visible behaviors (DCF) reported significantly higher ratings for the non-expert users' perceptions of the robot's performance.

### 4.5.3 Importance of Maintaining the Same IUs During the Encoding and the Recall of the PECP

Hypothesis 3 predicted that using a new ensemble of IUs "B" during the recall phase may lead to confusion while recalling the PECP, a longer time for rules retrieval and a greater period of time will be needed to achieve the task during the recall phase (when the PECP is supposed to be reused) in comparison to the situation when we use the same ensemble of IUs "A" that was used during the encoding phase (trial 1). Using a new ensemble of IUs "B" leads to worse human's perception of the robot's performance in terms of likeability, competence and social face support in comparison to the situation when we keep the same ensemble of IUs "A" that was used during the encoding phase.

This hypothesis corresponds to the setup 3 when the robot uses four different IUs each one assigned to one of the robot's visible behaviors during the encoding phase while in the recall phase the four different IUs used previously are changed by a new ensemble of other IUs that were never heard previously by the non-expert user. We included this hypothesis to highlight the importance of IUs maintenance and how implicitly changing it a bit may confuse a non-expert user. The robot used the condition DCF in trial 1 and changed the ensemble of IUs used in trial 1 during trial 2 by a new ensemble of IUs using the same technique DCF.

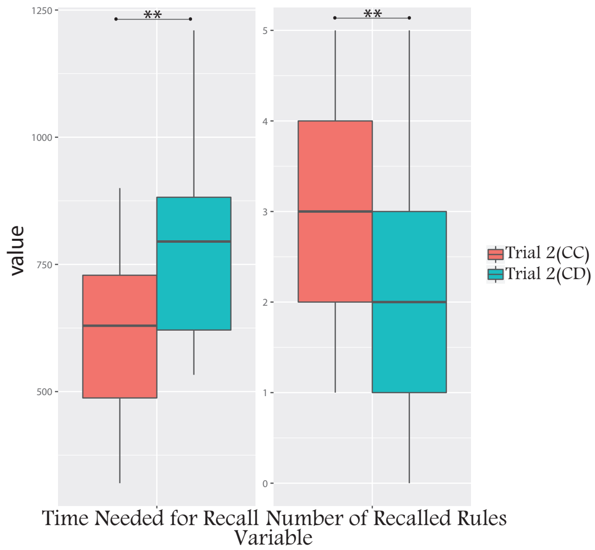



Fig. 4.9 The figure shows the first part of trials 2 objective results (number of recalled rules and the time needed for recall) corresponding to setups 2 and 3 (*:P-value<0.05, **:P-value<0.01, ***:P-value<0.001).

**Objective Results**

By comparing trials 2 objective measures of both setups 2 and 3, we remarked that there are statistically significant differences between trials 2 results of setups 2 and 3 in terms of number of recalled rules (t-test=2.94; p-value=0.005; d.f=38; effect size=0.93), time needed for the recall (t-test=2.91; p-value=0.005; d.f=38; effect size=0.92) and the task completion time (t-test=4.26; p-value<0.001; d.f=38; effect size=0.88).
Figure 4.9 shows the first part of trials 2 objective results corresponding to both setups 2 and 3 (number of recalled rules and the time needed for recall). Figure 4.10 shows the subjective results and the second part of trials 2objective results (task completion time) corresponding to setups 2 and 3. Based on figures 4.9 4.10, we notice that trial 2 of setup 3 gives lower results in terms of number of recalled rules and higher results in terms of time needed for the recall and task completion time in comparison to trial 2 of setup 2.
These results converge with our hypothesis 3. Changing the IUs ensemble used during the encoding phase (trial 1) in trial 2 (recall phase) leads to a decrease in the number of recalled

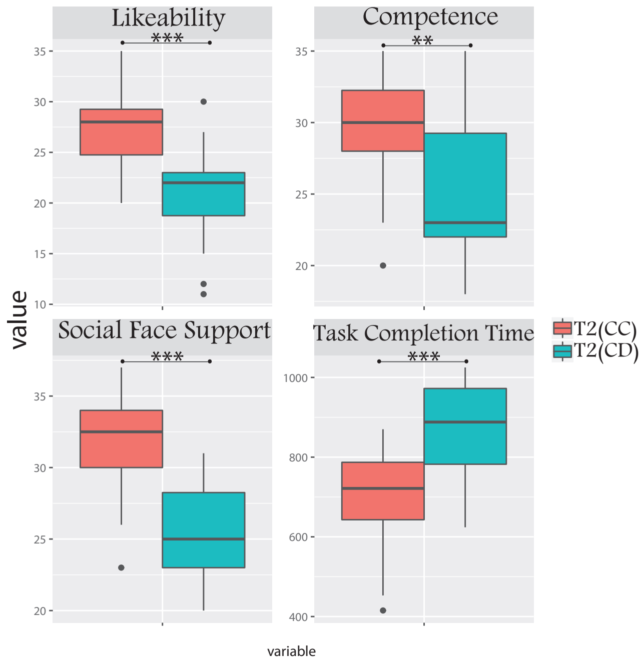



Fig. 4.10 The figure shows the subjective results and the second part of trials 2 objective results (task completion time) for both setups 2 and 3 (*:P-value<0.05, **:P-value<0.01, ***:P-value<0.001).

rules. It also leads to a longer time needed for the PECP recall and longer period of time needed to achieve the task in comparison to the condition when the minimally designed robot uses the same IUs during both phases the encoding and the recall phases (setup 2).

**Subjective Results**

By comparing trials 2 subjective measures, we remarked that there are statistically significant differences between trials 2 of setups 3 and 2 in terms of competence (t-test=3.49; p-value=0.001; d.f=38; effect size=0.8), likeability (t-test=4.83; p-value<0.001; d.f=38; effect size=1.55) and social face support (t-test= 5.34; p-value < 0.001; d.f= 38; effect size= 1.05).
Based on figures 4.9 4.10, we notice that trial 2 of setup 3 gives lower results in terms of competence, likeability and social face support in comparison to trial 2 of setup 2.
These results support our hypothesis 3. Participants answers during the debrief afforded some explanations for this decrease in ratings assigned by the non-expert users to the minimally designed robot. One of the participants indicated: "I suppose that the robot tries to make tricks because it changed the words that used previously. I tried to remember these

sounds and whether I have heard them before. Unfortunately, I think that I forget or the robot tries to frustrate me!".

### 4.5.4 IUs Wear-out and the Proposed Variation-Repeat Dually Coded Feedback

Hypothesis 4 predicted that IUs generated according to the variation-repeat IUs proposed technique (setup 4) lead to the same interaction outcomes during the encoding phase just like in the case when we combined constantly the same IU with the same robots' behavior (setup 2) so that a robot's instruction could be remembered correctly by non-expert users. We expect to have, when using such variation-repeat IUs technique (setup 4), the same performance in terms of PECP remembrance, time needed for rules retrieval and period of time needed for task completion time in comparison to when we use the technique DCF (setup 2). Also, we expect that when the minimally designed robot uses a variation-repeat IUs technique (setup 4), we will have higher ratings in the non-expert's perception of the minimally designed robot's performance in terms of likeability, competence and social face support in comparison to when the minimally designed robot uses the same IUs assigned to the robot's visible behaviors (setup 2)".

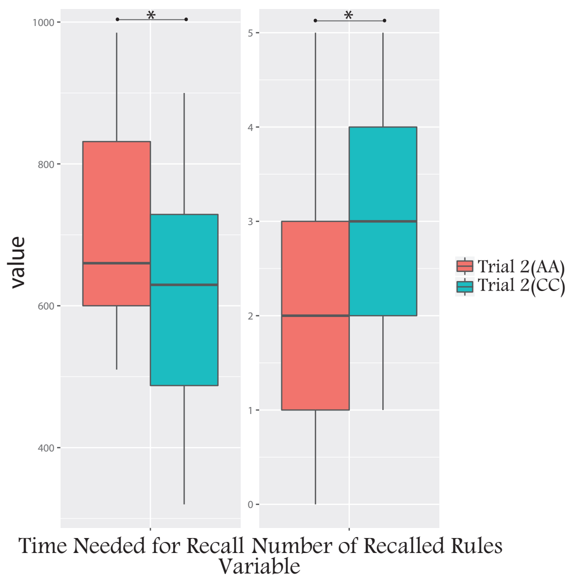



Fig. 4.11 The figure shows the first part of trials 2 objective results (number of recalled rules and the time needed for recall) of both setups 2 and 4 (*:P-value<0.05, **:P-value<0.01, ***:P-value<0.001).

### Objective Results

By comparing the objective measures, we remarked that there are statistically significant differences between trials 2 of both setups 2 and 4 in terms of recalled rules number (t-test= 2.56; p-value= 0.014; d.f= 38; effect size= 0.81), time needed for the recall (t-test=2.02; p-value=0.049; d.f=38; effect size=0.64) and the task completion time (t-test=2.02; p-value=0.028; d.f=38; effect size=0.72).
Figure 4.11 shows the first part of the objective results corresponding to trials 2 of both setups 2 and 4 (number of recalled rules and the time needed for recall). Figure 4.12 shows the subjective results as well as the second part of trials 2 objective results of both setups 2 and 4 (task completion time). Based on Figures 4.11 4.12, we strikingly notice that trial 2 of setup 4 gives lower results in terms of the number of recalled rules and higher results in terms of the time needed for the recall and task completion time in comparison to the values of trial 2 with the same measure values of setup 2.
These results do not meet our expectations included in hypothesis 4. Using a variation-repeat dually coded feedback technique (VRDCF) in a way that different IUs could mean the same instruction (knocking pattern) backfired and led to degraded performance.

### Subjective Results

By comparing trials 2 subjective measures of both setups 2 and 4, we remarked that there are statistically significant differences between trials 2 results of both setups 2 and 4 in terms of competence (t-test=2.59; p-value=0.013; d.f=38; effect size=0.81), likeability (t-test=5.32; p-value$<$0.0001; d.f=38; effect size=1.68) and social face support (t-test=4.56; p-value$<$0.0001; d.f=38; effect size=1.44).
Based on figures 4.11 4.12, we notice that contrary to what we hypothesized, trial 2 of setup 4 gives about lower results in terms of competence, likeability and social face support in comparison to trial 2 of setup 2. These results do not support our hypothesis 4.
Although, we enabled the robot with the capability of generating different IUs for the same behavior through the variation-repeat dually coded feedback technique to avoid message wear-out and to guarantee that the non-expert user enjoys the interaction, the results indicate that in terms of objective results, the performance is degraded where we have more PECP forgetfulness with such a technique in addition to the fact that non-expert users found that the robot is less competent, less likeable and less supportive for their social faces in comparison to the same constructs values in trial 2 of setup 2.
Participants of setup 4 indicated during the debrief that the robot was a bit entertaining the first time. However, during the second time (trial 2) of setup 4 some of the participants

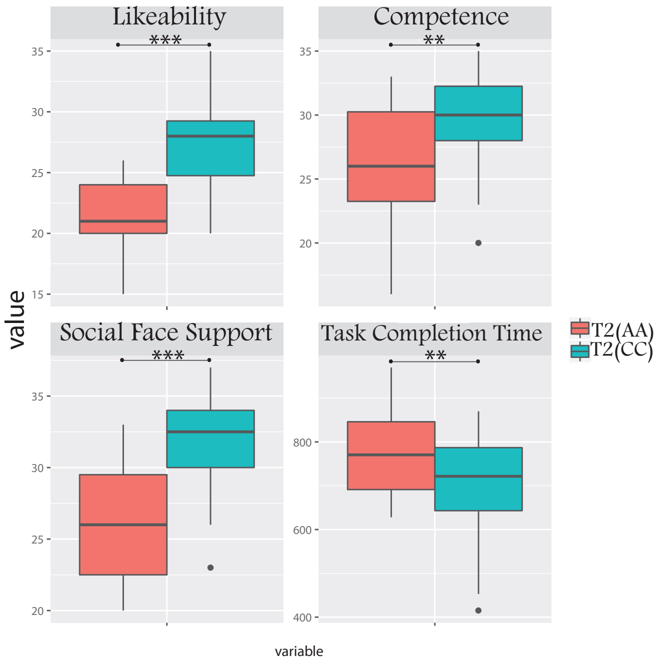



Fig. 4.12 The figure shows the subjective results as well as the second part of objective results of trials 2 (task completion time) for setups 2 and 4 (*:P-value<0.05, **:P-value<0.01, ***:P-value<0.001).

Table 4.1 Summary of hypotheses and results for primary measures.

| Hypothesis | Objective Measures | Subjective Measures |
|---|---|---|
| Hypothesis 1 | Supported Partly | Supported Partly |
| Hypothesis 2 | Supported | Supported |
| Hypothesis 3 | Supported | Supported |
| Hypothesis 4 | Not Supported | Not Supported |

revealed some insights which are related to the gathered results. One participant indicated: "I understand when the robot said something that it means having a chance to checkout the action before it is executed, however I get lost because I could not retain all the spoken sounds that correspond to the same action. There were a lot of sounds right!" This means that increasing the number of IUs per robot's behavior can backfire even if the human may like it the first time.

## 4.6 Discussion

### 4.6.1 Hypothesis 1: Illustration of PECP Recall Problem

Hypothesis 1 predicted that in a given task consisting of reusing a PECP, using the minimally designed robot's visible behaviors as the only feedback afforded to the non-expert user by the minimally designed robot would lead to poor PECP rules maintenance and would increase the task completion time during trial 2 in comparison to trial 1. In such a situation, the HRI mediocre process during the recall of the PECP leads to a poorer non-expert's perception of the minimally designed robot performance during trial 2 in terms of likeability, competence and social face support in comparison to the situation when the non-expert user used the minimally designed robot for the first time (trial 1).

The results provide conditional support for this hypothesis and, more importantly, suggest that although on an objective scale the performance was degraded, users still think that the robot is likeable and supportive for their social faces (Figure 4.6). In fact, by recalling some of the PECP rules, some participants felt that the robot was not frustrating since they succeeded even partly on guiding it to the different checkpoints without that they felt themselves obliged to put a lot of effort into reconstructing the whole CP during trial 2 (Figure 4.5).

Participants answers during the debrief support this insight. As the participants felt integrated during the HRI, they attributed positive traits to the robot during the debrief ("striving to finish the task", "slow but careful", "cute", etc..) which may explain the higher likeability results. This is in line with the human's asymptotic tendency to attribute positive feedback so that an agent such as a robot could succeed. Thomaz et al [44] highlighted this tendency that was noticed when a non-expert user was supposed to teach "sophie" the agent to achieve different tasks in the kitchen in the context of a game-based setup. In such a setup, users assign positive feedback to motivate the agent while it is just a virtual agent. Furthermore, participants could have attributed lower values in terms of the competence construct because we informed them that the robot is conceived to be used as a service robot that may help users suffering from Parkinson disease when they have to eat. When a robot is conceived to afford a service and the users are informed about that, it was proven that they adopt an utilitarian way [134] of judgment and a construct such as competence is related to the service "part" of the HRI (Table 4.1).

### 4.6.2 Hypothesis 2: Dually Coded Feedback to Increase PECP Recall

Hypothesis 2 predicted that IUs combined with the minimally designed robot's visible behaviors improve the PECP recall in shorter time and helps finishing the task swifter in comparison to the situation when only the robot's visible behavior (B) is the only feedback

afforded by the minimally designed robot to the non-expert user. Also, it helps to ameliorate the human's perception of the robot's performance in terms of competence, likeability and social face support (Table 4.1).
As expected, the results supported this hypothesis. Using a dually coded feedback helped with ameliorating the objective results in comparison to trial 2 results of setup 1. In fact, users could remember the PECP in a shorter time which led to a decrease in the task completion time (Figure 4.7). Participants who received a dually coded feedback reported significantly higher levels of social face support, competence and likeability (Figure 4.8) .

### 4.6.3 Hypothesis 3: Changing IUs Lead to a Worse HRI Outcomes

To verify whether hypothesis 2 higher results during trial 2 of setup 2 were related to the usage of IUs and whether IUs interfered in the PECP recall process, we elaborated Hypothesis 3. Hypothesis 3 predicted that using a new ensemble of IUs "B" during the recall phase may lead to a confusion while recalling the PECP, a longer time for rules retrieval and a greater period of time will be needed to achieve the task during the recall phase (when the PECP is supposed to be reused) in comparison to the situation when we use the same ensemble of IUs "A" that was used during the encoding phase. Using a new ensemble of IUs "B" leads to a worse human perception of the robot's performance in terms of likeability, competence and social face support in comparison to the situation when we keep the same ensemble of IUs "A" that was used during the encoding phase.
For this purpose, we compared trials 2 results of setups 2 and 3. The results support this hypothesis; users who performed the task in the presence of the same IUs during the encoding and the recall phase (setup 2) reported significantly higher levels of PECP recall, in a shorter time and the task was achieved quicker than those who performed the task when the IUs were changed. Subjective results were affected by trial 2 of the setup's 3 degraded performance (Figure 4.9). Users assigned lower values for the robot in terms of competence, likeability and social face support in trial 2 of setup 3 (Figure 4.10).
In fact, to be useful, a dual code should be preserved. For example, in our case we have the robot visible behavior as the pictorial first code related to the instruction (knocking pattern), the second code is the IU. If we suppose that we want the user to remember the instruction needed at time T, and that a robot's behavior (pictorial code) could not be displayed because the goal is to reduce the wrong steps, since steps are costly in terms of robot's energy, time and may cause frustration if they are wrong, one can directly deduce that an IU that it is generated before the robot executes any behavior could be suitable to refresh the non-expert user's memory so that they can remember the adequate composed instruction (knocking pat-

tern) that it is associated with the intended behavior before it is too late and the robot starts executing a wrong behavior (Table 4.1).

### 4.6.4 Hypothesis 4: Variation-Repeat Technique Backfires

Finally in the context of hypothesis 4, we conducted a comparison between trials 2 results of setups 2 and 4 that aimed to provide further insights into the question of whether using a variation-repeat dually coded feedback strategy leads to the same interaction outcomes in terms of objective performance and subjective evaluation.

Hypothesis 4 predicted that IUs generated according to the variation-repeat IUs proposed technique (setup 4) lead to the same interaction outcomes during the encoding phase just like in the case when we combined constantly the same IU with the same robots' behavior (setup 2) so that a robot's instruction could be remembered correctly by non-expert users. We expect to have, when using such variation-repeat IUs technique (setup 4), the same performance in terms of PECP remembrance, the time needed for rules retrieval and the period of time needed for task completion time (Figure 4.11) in comparison to when we use the technique DCF (setup 2). Finally, we believe that when the minimally designed robot uses a variation-repeat IUs technique (setup 4), we have higher ratings related to the non-expert's perception of the minimally designed robot's performance in terms of likeability, competence and social face support (Figure 4.12) in comparison to when the minimally designed robot uses an IU per robot's visible behavior (setup 2)".

Results contrast with this hypothesis. Although, our goal was to avoid the wear-out messages problem, using different IUs assigned for the same robot's behavior backfired and led to worse PECP recall for a longer time and increased the task completion time. In line with the objective results, subjective evaluation dropped in trial 2 of setup 4. This degraded performance could be related to the fact that the participant's memory could not retain all the IUs per one behavior. The remembrance problem when using the variation-repeat technique was mentioned in 80% of the participants speech while being debriefed (setup 4). This indicates that using the same IU per one robot's visible behavior is safer if we want to increase the PECP recall (Table 4.1).

## 4.7 Implications of the Results

The findings suggest that non-expert users must have more expressive feedback rather than mere feedback that consists of the robot's visible behaviors for increasing the PECP remembrance in order to sustain intrinsic motivation to assign higher subjective evaluation related

to the human's perception of the robot's performance.
When users have no feedback other than the robot's visible behaviors, they characterize the robot as non competent and the overall HRI performance is rather stable or degraded because non-expert users cannot remember the PECPs. The current experiment provided users with four setups to evaluate their performance: no dual coded feedback (setup 1), dual coded feedback (setup 2), modified version of IUs during the recall phase (setup 3) and the variation-repeat technique (setup 4). Users who did not receive dual coded feedback had reported the lowest levels of PECP recall and time needed to recall. Users who did receive dual coded feedback reported an increase in PECP recall and thus an increase as well in the overall performance. The somewhat encouraging finding is that when we change the IUs, the objective and subjective results are affected which highlight that IUs usage with minimally designed robots activates the memory related to dual coded rules recall [105]. Furthermore, the effect of the VRDCF technique backfired; that is, giving many IUs for the same robot's behavior did not provide any additional increase in objective or subjective results which we should as a conclusion avoid to do with minimally designed robots if we want to increase the PECP recall and the human's perception of the robot.

## 4.8 Limitations

Although these results suggest that minimally designed robots should provide non-expert users with dual coded feedback, this approach might have three drawbacks. First, research on dual coding suggests that dual coding is most effective when the human is capable of building referential connections between the information and the codes. Building referential connections between IUs and the robot's visible behaviors includes some cognitive effort. That it is why increasing the number of rules could be useless and more harmful.
Second, another problem that we have not encountered while conducting our experiment that it is related to socially anxious non-expert users. In fact, people who suffer from social anxiety have a sickly state that it is activated when they are anxious. Such people predict and imagine the worst when they have to recall information which may lead to drastic performance if we use the dual coded feedback method to encode on the memory rules of interaction and later implicitly drive them to recall these rules [135].
Third, our evaluation focused on testing only the effects of the proposed dual coded method on participants who have low cold-heartedness. In fact, in [136], Aziz-Zadeh et al suggested that the perception and recognition of IUs are affected by the human's cold-heartedness level. Cold-heartedness is one of the constructs of the Personality Inventory-Revised (PPI-R) [137]. The PPI-R cold-heartedness scale was used as an additional measure of affective

empathy, and it was proven that it would negatively correlate with IUs perception. That it is why, we plan to extend our work to explore a more diverse set of cold-heartedness levels and long-term effects of the proposed strategies on PECP recall.

## 4.9 Conclusion

As robots move into roles that involve providing users with services, such as cleaning the floor and working in offices, they need to employ strategies for affording an effective expressive feedback to facilitate communication with them. In this work, we described two key feedback strategiesDCF and VRDCFbased on observations of human-human interactions and social psychology theories. We implemented these strategies on a robot that cooperatively interacts with its users to visit different checkpoints marked on the table. We measured the interaction outcomes in terms of the objective performance and subjective evaluation of the robot. Our results showed that, when the robot combined IUs and the robot's visible behaviors, participants completed the task faster and assign higher ratings for the robot. We also found that using the VRDCF strategy increased the time needed to recall the PECP, as the PECP is recalled incorrectly and the human's perception of the robot's performance was mediocre. We believe that increasing the number of instructions results in a tradeoff between cognitive load and breakdowns related to memory struggles during the recall of the PECP when there is a high number of rules that need to be recalled. This suggests that robots should selectively use these strategies based on the goals of the instruction.
Based on the previous studies, we may confirm that using IUs help to gracefully mitigate communication protocol reuse and help establishing long term communication protocols. However, to be able to predict whether there will be future interaction instances during which the communication protocol could be maintained, we need to verify whether people feel attached to the minimally designed robot. In fact, emotions provide a feedback system. For example, they may help us to learn how to maximize the outcomes while interacting with others. Emotions promote belongingness and good interpersonal relationships and thus people may feel attached to a task, a person or simply a social agent. In our next study, we will explore whether using IUs and the robot's visible behaviors (VBs) help on increasing people attachment to a minimally designed robot. Positive emotions (such as attachment) that people may feel are the motivator to develop some empathy during the interaction for the robot. They can help people put forward some effort to remember the encoded rules. Consequently, it is essential to measure whether such positive emotion emerge or not.

# Chapter 5

# Exploring Attachment Evolvement for a Minimally Designed Robot

## 5.1 Introduction

Social bonding suggests that taking part in a communication increases the attachment and consequently the adaptation capability which may enhance the meaning acquisition process [138]. As an example, infants who form a social bond with their caregivers establish a better sense of their surroundings. In fact, slowed voice tones and physical contact, help the child to establish a preference for the caregiver and a mutual interest in communication evolves [139]. In such scenarios, children distinguish the different voices, and turn their heads to pick up the tones. They can intentionally generate imitations of hand gestures and voice sounds, with different expressions transferring a knowledge, an interest, an excitement, etc. [140]. Meanwhile, caregivers, excited by the infant's expressions, respond with affectionate behaviors by using rhythms of speech and slowed gesture with a soft voice and a moderate modulation of pitch [141]. Incrementally, the attachment evolves and the mutual understanding occurred by mirroring the patterns of each others' expressions [142]. Another similar example that involves the attachment process is the human-pet relationship. Many studies [143][144][145] investigated the beneficial effects of pet ownership on human's interpersonal relationships and explored the importance of the human-animal interaction for the human's relational development [144][145][146]. Sparks et al [146] defines the behavioral attachment during the human pet interaction [1] as a prominent factor that helps the human to understand the pet's signals. It is then reasonable to presume that attachment between the

[1] Behavioral attachment: It consists on the human's involvement in different tasks with their pets such as play or teaching them new instructions where the pets are using their inarticulate sounds and their bodies movements to transfer the meaning to the owner

human and others plays a unique role that helps on understanding others and the environment.

In this vein, we are interested in understanding whether inarticulate sounds and simple gestures help to establish the attachment process between the human and our mobile accompanying robot. We believe that we can use them to create a social bond just like in the caregiver-child or the human-pet scenarios and then enhance the adaptation within the human-robot interaction. Designing a robot that is not related to any language or any special cultural behaviors, will afford the chance to create a universal form of communication for the human-robot interaction just as in the child-caregiver scenario that is based on the attachment between both parties and the use of simple cues to establish online the customized social rules. To measure the social bonding, we intend to assess the values of five factors : the degree of adaptation to the social creature, the stress felt by the subject, the friendliness of the robot, the cooperation and the achievement degrees.

## 5.2 Background

Many studies investigated the attachment of humans to social robots [9][147]. Sung et al [147] indicated that people had a tendency to name their robots. Findings such as this suggested that people may treat robots like they treat a child or a pet [148]. In fact, if the robot exhibits a social behavior, a social bond will be formed and then people feel more comfortable with robots [149]. As an example, Samani et al [149] proposed Lovotics, a robot that uses audio and touch channels along with internal state parameters in order to establish long standing bonds with individuals. Lovotics afforded for the users an intimate relationship and people felt so comfortable that they even hugged the robot. Hiolle et al [150] used the Sony AIBO robot during their experiment where they showed that people tend to form a social bonding with needy robots that demanded assistance from users. The latter study suggests that robots do not need multi-modal communication to develop the attachment process and that exhibiting a simple behavior can be attractive enough for the human to feel attached to the robot and to embark on a positive constructive relationship with its. In our study, we will use similar simple behaviors that can be assembled under the immediacy cues category: the gestures and inarticulate sounds. We want to explore whether these two social cues can help to ground the attachment process and explore the social bonding's effect on the interaction's meaning acquisition. Inarticulate sounds were used to establish playground language with autistic children [13] and were studied in the context of the human-computer interaction [115] where it was proved that it can lead to a

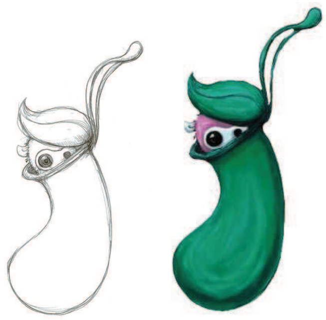


Fig. 5.1 ROBOMO's design.

Table 5.1 The different behaviors that ROBOMO can exhibit.

| Code of the Behavior | Behavior | Description of the Behavior |
|---|---|---|
| IS | inarticulate sounds | yes, no, right, left, forward |
| ND | nodding | en..well, thank you, I'm not sure |
| GS | gestures | turning left, turning right |

compassionate effect. Iconic gestures [151] [2] facilitates the human-robot interaction [152] and were used in different contexts such as hosting activity [153], showing hesitation [154], etc... In our current work, we intend to ground the attachment process that may evolve between ROBOMO and the participants. We want to verify whether a social bonding can emerge in the context of the human-ROBOMO interaction and whether it can guarantee to transfer the meaning once meshed with the iconic gestures and the inarticulate sounds.

## 5.3 ROBOMO Design

We respected the minimal design paradigm which consists on reducing the robot's design and preserving only the most elementary components [115]. ROBOMO has a long shaped body with an attractive container (made of plush) and has no arms. We had intentionally given ROBOMO a pitcher plant (Nepenthe) appearance to encourage people to interact with it, much as one might with a young child or a pet. We believe that exposing a half hairy head (Fig. 5.1), makes the robot looks cute and affords a starting point for the social bonding process formation. Although used for personal navigation, our accompanying mobile robot is not designed to walk which may create a sort of an empathetic feeling towards ROBOMO. Inarticulate sounds were produced according to Okada et al's [129] generation method of

[2] They are speech-related gestures that mention concrete objects for example showing the direction for the human.

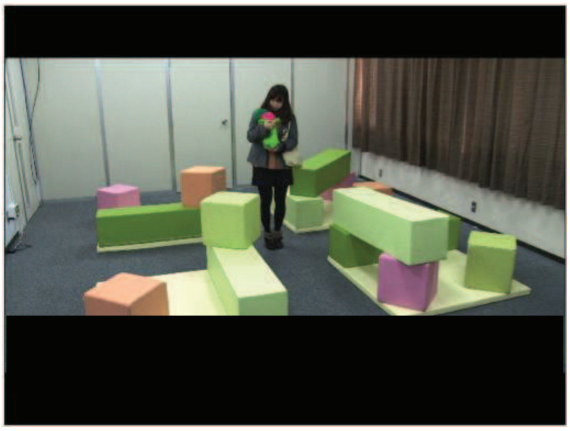


Fig. 5.2 A snapshot of our mobile accompanying robot interacting with a participant during the experiment.

inarticulate sounds. Three types of behaviors were exhibited (i) the inarticulate sounds with meaning (ii) the nodding (iii) gestures (table 5.1).

## 5.4 Experimental Protocol

The main objective is to explore the effectiveness of the attachment process and its impact on the meaning acquisition within a human-robot interaction. We expect that gradually, the communication will be clearer. We setup an indoor ground for navigation task that contains cross points (Fig.5.2). To pick the right behavior, the participant is instructed by the robot. We asked the participant to talk to ROBOMO with simple words and slowly. 12 participants with age varying in $[22-30]$, take part in 3 sessions. We have chosen several configurations during the 3 sessions to guarantee the diversity of the participant's responses. It helps also to ensure that any successful meaning guessing of ROBOMO's behaviors is not related to the fact that we are using the same configuration but it is related to the social bonding which enhances the participants' adaptation. In our scenario, if the human does not perceive the robot's response, he will repeat his question within a short period for direction's confirmation. In such case, the robot exhibits a body behavior such as pointing to the left or right direction using its upper body part combined with the right inarticulate sound as a response. On the other hand, in the short periods of silence (when the user is not addressing any request), a nodding behavior is displayed. Each student interacts with ROBOMO for 2 minutes and then answers the same 5-Likert Scale questionnaire (13 questions). The table 5.2 contains the different questions.

Table 5.2 The questionnaire evaluating the attachment's five factors.

| Factors | Code | Questions |
|---|---|---|
| Cooperation | Q1 | Has ROBOMO tried the best it can to help you? |
| | Q2 | Do you feel that ROBOMO needed your help? |
| | Q3 | Have you wanted to help ROBOMO? |
| Achievement | Q4 | Had you recognized the direction indicated? |
| | Q5 | Can you distinguish ROBOMO behaviors' different meanings? |
| | Q6 | Do you think that you established a good relational contact? |
| Friendliness | Q7 | Can you consider ROBOMO as a friend? |
| | Q8 | Have you felt that ROBOMO was familiar for you? |
| Stress-Free | Q9 | Was it hard for you to understand ROBOMO? |
| | Q10 | Can you get the feeling of ROBOMO? |
| Adaptability | Q11 | Do you think that ROBOMO is a smart robot? |
| | Q12 | Can you feel that ROBOMO showed some animacy? |
| | Q13 | Do you think that ROBOMO behaved like a baby? |

Our evaluation of the social bonding process is articulated around five factors: the adaptation, the stress, the friendliness, the cooperation and the achievement. We tried to record on log files the participants' requests and the robot's instructions. We recorded also the interaction videos that helped us to detect the spatial points when the gestures were used.

## 5.5 Results

### 5.5.1 Questionnaire Based Results

To statistically identify the most ameliorated social bonding factors, we applied ANOVA based on the users' answers. Table 5.3 exhibits the different p-values and the Fig.5.3 displays the average mean opinion score (MOS) values of the different subjects per session where the horizontal axis shows the social bonding five factors combined with their related questions during the three sessions and the vertical axis shows the MOS values for 12 subjects. The MOS is the arithmetic mean of all the individual scores, that ranges from 0 (worst) to 5 (best) where a value that is equal to 3 is acceptable.

Based on the Figure5.3, we can see that cooperation, achievement and stress-free factors slightly went up by means of sessions. Table 3 showed that, the questions Q1, Q2 and Q3 which evaluate the cooperation factor were statistically significant with p-values respectively equal to ***$p=0.0024<0.005$; *$p=0.0927<0.1$ and *$p=0.0993<0.1$. The questions evaluating the achievement (Q4, Q5 and Q6) showed also significant results with p-values respectively equal to ***$p=0.001<0.005$, *$p=0.0615<0.1$ and **$p=0.0137<0.05$. Finally, the

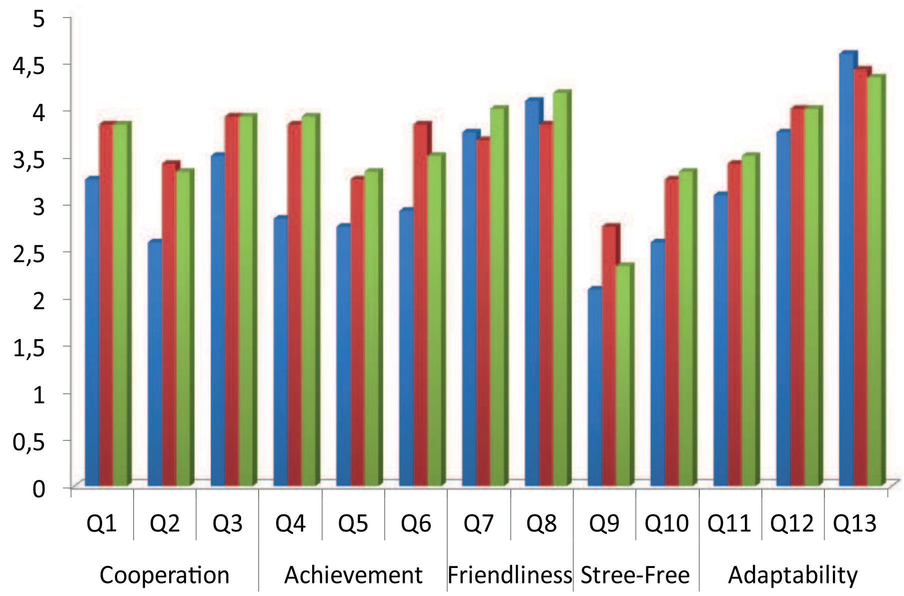



Fig. 5.3 Results of the average mean opinion score (MOS) based on the 13 questions' answers and for the 3 sessions of the experiment.

questions that concern the stress-free (i) Q9: **p=0.0391<0.05 (ii) Q10: **p=0.0185<0.05 showed also that there were statistically significant results. These results suggest that the robot's cooperation capability using the inarticulate sounds and the gestures helped on achieving the task and leaded to stress reduction while interacting with ROBOMO.
Based on the Figure.4, we can see that friendliness and adaptability increase slightly while statistically there was no significant differences between the different sessions with respectively (i) Q7: p=0.2439 (ii) Q8: p=0.1573 for friendliness and (i) Q11: p=0.2038 (ii) Q12: p=0.2875 (iii) Q13: p=0.4785 for adaptability. We asked from people to write down their opinions before and after experiment. We analyzed the participants' different subjective answers and we found out that users confirm that it is easy to adapt with ROBOMO. They found its friendly and cute before even starting the experiment. Thus, the robot's appearance played a key role to reduce the adaptation gap and to give a good first impression.

### 5.5.2 Real Time Interaction Results

Based on the stored log files of the speech recognition system and the recorded videos, we counted the user's picked directions based on the robot's indications and the related robot's behaviors (getures, nodding, inarticulate sounds) (table 5.4) We used the data of the table 4 to evaluate the relationship between participants' behaviors and robot's behaviors. Table

Table 5.3 ANOVA evaluation of the questionnaire results

| Factors | Code | P-value | Results |
|---|---|---|---|
| Cooperation | Q1 | $*p = 0.0927 < 0.1$, d.f=11 | significant |
| | Q2 | $***p = 0.0024 < 0.005$, d.f=11 | significant |
| | Q3 | $*p = 0.0993 < 0.1$, d.f=11 | significant |
| Achievement | Q4 | $***p = 0.001 < 0.005$, d.f=11 | significant |
| | Q5 | $*p = 0.0615 < 0.1$, d.f=11 | significant |
| | Q6 | $**p = 0.0137 < 0.05$, d.f=11 | significant |
| Friendliness | Q7 | $p = 0.2439$, d.f=11 | not significant |
| | Q8 | $p = 0.1573$, d.f=11 | not significant |
| Stress-Free | Q9 | $**p = 0.0391 < 0.05$, d.f=11 | significant |
| | Q10 | $**p = 0.0185 < 0.05$, d.f=11 | significant |
| Adaptability | Q11 | $p = 0.2038$, d.f=11 | not significant |
| | Q12 | $p = 0.2875$, d.f=11 | not significant |
| | Q13 | $p = 0.4785$, d.f=11 | not significant |

Table 5.4 The contingency table integrating the human behavior and the related robot's behavior during the 1st, 2nd and 3rd sessions

| | Session 1 | | | Session 2 | | | Session 3 | | |
|---|---|---|---|---|---|---|---|---|---|
| | Human Behaviors | | | Human Behaviors | | | Human Behaviors | | |
| Behaviors | Forward | Left | Right | Forward | Left | Right | Forward | Left | Right |
| IS | 9 | 13 | 12 | 13 | 20 | 32 | 9 | 12 | 27 |
| Nodding | 13 | 12 | 18 | 14 | 7 | 11 | 16 | 12 | 13 |
| Gestures | 12 | 6 | 21 | 11 | 11 | 10 | 7 | 17 | 11 |

Table 5.5 Chi-Square test of independency and the corresponding P-values evaluating the relationship between the human behaviors and the robot's behaviors during the different sessions of the experiment.

| Sessions | Chi-Square Values | P-Values | Results |
|---|---|---|---|
| Session 1 | $\chi^2$=5.21, dof=4 | $p = 0.266$ | not significant |
| Session 2 | $\chi^2$=7.53, dof=4 | $p = 0.110$ | not significant |
| Session 3 | $\chi^2$=12.2, dof=4 | $p = 0.016 < 0.05$ | significant |

5.5 shows the different Chi-square test's results where we can see that gradually the p-value increases by means of sessions: $p1 < p2 < p3$ with a statistical significance during the third session. We noticed also that there was no significant results during the two initial sessions. This incremental p-value increase suggests that gradually a strong relationship evolves between the human and the robot's behaviors.

### 5.5.3 Correspondence Analysis Results

In order to visualize the relationship between the robot and the users' behaviors, we used a visual approach which is the correspondence analysis. The bi-dimensional map exposed the relationship among categories spatially on empirically derived dimensions. The frequency for each category (*forward*, *right*, *left*) and for each variable (nodding, inarticulate sounds (IS) or gestures) is considered in order to expose the Euclidean distance in two dimensions. Figure 5.4 depicts the associations between categories of robot's behaviors and participants' picked directions during the three trials. The red triangles represent the participants' chosen directions and the blue dots represent the robot's behaviors. Considering the first trial's correspondence analysis Fig.5.4 (left), we can see that there was no clear relationship between the robot's behaviors and the human's chosen directions. By analyzing the second session results Fig.5.4 (center), we can see that the robot's behaviors starts to be mapped with the human chosen directions. In fact, there is a tendency to attribute the nodding behavior with the *left* direction, the inarticulate sounds with the *right* direction while the gestures were associated with the *forward* direction. During the final session Fig.5.4 (right), the Euclidean distance between the robot's behaviors and the human chosen directions becomes shorter and the tendency to associate for each direction a specific robot's behavior becomes clearer. In fact, human turning *right* behavior was related to inarticulate sounds, turning *left* was associated with the nodding, while going *forward* occurred when the robot exposes gestures.

## 5.6 Discussion

Based on the questionnaire results (Fig.5.3 and table5.3), we noticed a gradual amelioration on the human's attachment process. The stress was decreasing during the interaction (Fig.4) which explains the different significant p-values (p=0.0391, p=0.0185). Cooperation had also significant values with p=0.0024, p=0.0927 while achievement p=0.001, p=0.0615. This highlights the effectiveness of using inarticulate sounds and iconic gestures to decrease the stress, encourage the human to cooperate with the robot in order to achieve the task

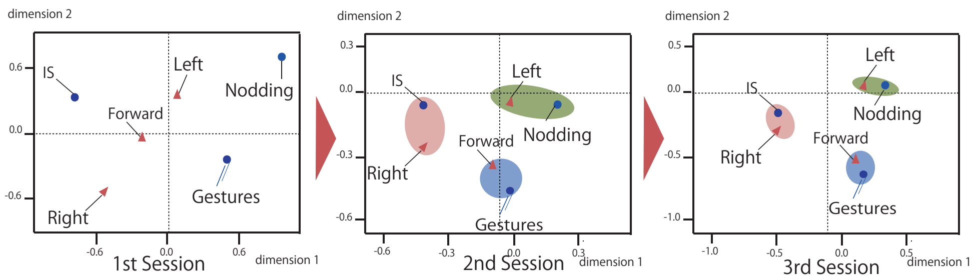



Fig. 5.4 The correspondence analysis of the trial 1 (left), trial 2 (center) and trial 3 depicting the association between the robot's behaviors (inarticulate sound and gestures) and the directions (forward, right, left).

and thus helps on creating a social bonding during the human-robot interaction which may facilitate the meaning's acquisition. In fact, we remarked a common interest on finding the frequent successful patterns combining for each robot's behavior a particular direction. Based on the table 5.5, we remarked that there was an increasing tendency to associate the robot's behaviors with the available directions during the navigation task $(p1 < p2 < p3)$. The incremental formation of attuned patterns which maps the robot's behaviors with the human's chosen direction was clearer during the sessions 2 and 3 as the Fig.5.4 shows. Our experiment leads us to the conclusion that our accompanying mobile robot succeeded in eliciting positive and affectionate behavior from participants. We conclude then that the inarticulate sounds and gestures that were used by ROBOMO during this dyadic interaction appeared sufficient for the attachment evolvement and helped on acquiring the meaning of the robot's behaviors.

## 5.7 Conclusion

Our study explored the human's attachment toward our accompanying robot. ROBOMO used inarticulate sound and iconic gestures in a desynchronized way in order to help people navigating in a block-based environment. It was surprising to see no anxiety-avoidance type of attachment existing in the participants towards ROBOMO which helped to decrease the stress and strengthens the human-robot cooperation in order to achieve the task. The results showed that inarticulate sounds and iconic gestures helped on grounding the attachment process during the experiment and that the participants gradually acquire the meaning of the robot's behaviors so that a communication protocol could finally be established. However, we remarked that there were no special significant results in terms of friendliness and adaptability. We may explain so, by the fact that the gestures and robot's IUs were not synchronized so that the human feels that the robot is adaptive and friendly. In our next work, we will try to measure not only the attachment but also 3 other factors which are belief, commitment and involvement and which are related to the social bonding. In fact, social bonding theory consists of not measuring only the attachment but 4 factors including the attachment. In the HRI community and to the little of our knowledge, there were no tools created to measure the social bonding's four factors. That it is why one of the issues of our next study will be the establishment of a complete social bonding questionnaire measuring the 4 factors. After, we validate our tool, we use it in a case study, to verify whether it is better to have a minimally designed robot that it is proactive or reactive. Our robot in the next study, will be synchronizing the robot's gestures with the IUs to verify whether we have an increase in terms of attachment factors by means of interaction instances.

# Chapter 6

# Exploring Social Bonding's Four Factors And the Prosociability Effect

## 6.1 Introduction

It has become increasingly apparent that, designing robot behaviors that trigger bonding with humans is a necessary requirement in many application areas and contexts where robots need to interact and collaborate with humans [155][156]. Such robot leading to social bonding formation may trigger a positive reaction from humans and lead to a positive human-robot relationship (HRR) [157]. In fact, in daily life, a human's positive attitude toward others is driven by the social bonding that evolves during their interactions. Social bonding is an indirect trigger that leads to a reciprocation of another's kindness with a noble act and brings about a more positive human-to human relationship.

In this context, we want to investigate whether similar social bonding can evolve between a human and a robot so that we can ensure that users will reciprocate the robot's attempts to achieve the task by agreeable reciprocated acts and whether it may lead to a positive HRR.

Travis Hirschi's social bonding theory argues that, people who *believe* in societies rules, are *attached* to others. Therefore, they have a high *commitment* to achieve conventional activities and reciprocate the agreeable gestures of others [138]. They can feel highly *involved* in their daily life so that, they begin to invest more time and energy in activities which serve to further bonds with others. As a result, less time is left for them to become involved in deviant activities [158]. Gottfredson and Hirschi [159] proved that people who have a weak bonding are more likely to deviate and have bad relationships with others.

On this basis, if we design the robot's behaviors in a way that we measure the social bonding evolving each time we integrate a new behavior in the robot's behavioral design, we can

then have the capability to detect the most prominent behaviors yielding to a better social bonding formation, and as a result, to a more positive Human-Robot Relationship (HRR).
Two communication channels are integrated in our robot, called ROBOMO, which are inarticulate utterances (IUs) and some gestures (Gs), while we try to measure the social bonding each time we use one or both of the communication channels.
The proposed four elements metrics measuring social bonding should converge in order that we may validate the usability of the proposed metrics and in order for us to guarantee the reliability of such suggested metrics to measure the social bonding each time we need to add a new behavior to the robot and to judge whether it is a useful behavior that increases social bonding or not. Another study that joins the same insight is the Belapeme et al [160] study where he confirms that synchronizing different communication channels may increase social bonding.
Furthermore, models from social psychology describe how humans predict the events and behaviors of other humans [161]. That it is why, a reactive accompanying robot would be preferred over a proactive accompanying robot since a human may feel that they control the situation and may predict the robot's behavior. A robot can be reactive if it responds in a timely manner to changes in the external asynchronous human's requests. It cannot anticipate neither has it any kind of task planning ability because it can only react and, for example, it cannot take a decision to initiate an interaction. A proactive robot can be defined as a robot that may propose for the human to undertake some tasks or to engage in a conversation without the human emitting any request to make the robot propose such suggestions. However, the proactivity of an accompanying robot can be thought to be equally important in order to induce the human's engagement in the interaction when the accompanying robot initiates a conversation.
Therefore, the current study is concerned with the issue of exploring the effect of 'reactive' and 'proactive' response modes adopted by the robot on the social bonding evolving during the interaction with a minimally designed accompanying robot. If the proposed metrics measuring the social bonding are validated in the first step (when we tried to measure the bond evolving when IUs and Gs are combined) assessing which type of behavior ('reactive' or 'proactive') an accompanying minimally designed robot should adopt to increase bonding should be both straightforward and reliable since we intend to use the validated proposed metrics.

## 6.2 Related Work

Since the proposed study and its experimental evaluation is motivated by theories from social psychology and previous concepts and studies from HRI, this section provides an overview on relevant theoretical foundations in human-human interaction, design concepts and HRI related studies.

### 6.2.1 Social Bonding

Hirshi [138] attempted to measure bonding using four elements which are 'attachment', 'commitment', 'belief' and 'involvement' in the context of high school students. He defined attachment as the emotional linkage between a person and society, commitment as the effort a person puts forward in social activities, belief as the person's conviction that a particular social activity or task is useful and involvement as the extra time and energy being put forward in order to prove that they are highly implicated in society. Hirshi [138] found that measures of attachment (caring, relaxation and likeability), commitment (average of grades, participation in school activities), belief (respect for social rules) and involvement (extra school tasks the student does as they become adapted to the school atmosphere), help with predicting a student's delinquency. He highlighted that measuring only one element does not permit accurate predictions of future human-society relationships [138].

Many studies adapted Hirschi's theory of social control in order to consider studying the bonding between humans and robots. Bethel et al, [162] investigated whether children were able to share a secret with a robot. The results indicated that, children were likely to share the secret and that they interacted with it in a similar way as they would with a caregiver. Similarly, Swerts et al [163] investigated whether children considered playing with the robot to be like playing with a friend. The results suggested that children enjoyed playing with the robot more than playing alone but not better than when playing with a friend. In another HRI study, the robot's ability to establish and maintain a social bond with a child was examined in the context of a hospital [160]. Results suggest that children become accustomed to interacting with the accompanying robot and a bonding evolves during the interaction. Fior et al [164] investigated whether children could form relationships with robots and view them as friends. Their results showed that most children thought the robot could be t heir friend and almost half of the children would even share a secret with the robot. Kanda et al [52] conducted a child-robot experiment at a Japanese elementary school using two "Robovie" robots with first-grade and sixth-grade children. They wanted to investigate the possibility of using accompanying robots as social partners to teach the children the English language. Although the majority of the children did not improve their English skills, the children were attached to the robot. Up to now, research studies in HRI focused on only one element to predict bond evolvement, being attachment. However, Hirshi [138] highlighted that we need to explore the evolvement of four factors (belief, attachment, commitment and involvement) and not only the attachment factor in order for us to determine the evolvement trends (positive or negative) of the social bonding. Another point that we tackle in our research concerns the bonding evolving between adults and an accompanying minimally designed robot rather than to use the classical condition where only the social bonding between children and the robot is studied.

### 6.2.2 Accompanying Robots and the Issue of Minimal Design Paradigm

In the last few years, most of the studies have focused on the goal of building social accompanying robots that have an enormous number of communication channels and which can be safely operated [165][166]. By accompanying, we mean a robot that stays close to the human because the task (or the service that need to be afforded for the human) requires that. Some studies [167][168], examine how a speaking accompanying robot can infer adequate speech by combining words to particular contexts in different situations. In some other studies, vision-based scene understanding and language recognition are combined and integrated in the accompanying robot [168][169] in order to make it adaptive to human preferences. Kanda et al integrated such a combination of vision-based scene understanding and language recognition in an accompanying robot called Robovie in order to investigate the HRI in a museum [170] and a school [171]. Although using numerous sensors can be a key element to realize an advanced accompanying robot, such an accompanying robot would not be affordable[1] for common users.

We need to build affordable accompanying robots that are expressive enough to satisfy the user and induce human social bonding [172]. In addition to the desire to design affordable robots, rather than expensive robots that possess a high number of sensors and effectors, we should consider as robotists that this leads to the emergence of complex interaction patterns and may further lead to anomalies during the HRI if the robot exposes a combination of complex patterns that it is not handled or accepted in daily life (e.g: the situation when the robot uses inadequate speech for the situation). That is why one key concept in our work needs to be highlighted here; that being minimal design. The minimal design concept can be defined as the minimization of the robot's appearance and communication channels in its use of anthropomorphic features so that humans do not overestimate or underestimate its skills. This was first proposed by Okada et al [8]. So, in our current work, we are pri-

[1] By affordable, we mean that increasing the number of sensors and effectors would increase the manufacturing cost of robot and once commercialized, common users would consider it to be unaffordable.

marily interested in minimally designed (minimal number of sensors and anthropomorphic features) accompanying (it has to assist the human and be close to him during the service attribution) robots.

### 6.2.3 Reactive versus Proactive Accompanying Robots

We define a proactive behavior as taking the initiative, whenever it is necessary, to achieve a task. It is a means to satisfy internal social aims [173], but also to engage with others. Moreover, it can often be embarrassing when you need to ask someone to help you. Therefore, we believe that a proactive accompanying robot can be more appreciated than a reactive accompanying robot. Providing the accompanying robot, with an ability to offer proactive behaviors for humans, is one of the most important topics within the HRI community [174]. Satake et al [174] proposed a model of approaching behavior to initiate a conversation with walking pedestrians. Another topic concerns the study of the appropriate moment to start an interaction [175]. Several works consider when to decide to initiate a conversation with the human depending on their trajectory or the distance to the accompanying robot [176]. Estimating intended human motion was used to enable an accompanying robot to give proactive assistance to an active human partner [176]. Achieving the proactive behavior of agents through goal reprioritization is suggested in [177].
Although we expect that proposing proactive behaviors may ensure a better bonding between humans and robots [178], we must also lend support to the claim that, using a socially reactive robot might be more valued. In fact, an accompanying robot that acts like a friend and provides us with proactive behaviors is much more complicated to achieve [179]. It requires to attract a real personality to attract the user [180]. Therefore, people can adopt a negative attitude towards proactive accompanying robots because they are more lifelike [178]. People could fear that proactive accompanying robots could lose control and threaten them [181]. In fact, proactive accompanying robots make decisions of when trigger an interaction with a person, thus potentially leading to situations where users' may perceive that they are not in control of the interaction [177]. An overview of such issues, such as controllability, privacy, and transparency is provided by [182]. In fact, control is also crucial in maintaining a good HRR. As an example, the Microsoft Office Paper-Clip assistant "Clippy" was evaluated as being annoying because of it being a proactive agent that indirectly controls the users of Microsoft Office attention, however, users indicated that they would in fact, prefer a reactive "Clippy" [183]. Essentially we are particularly interested in another topic that being the investigation of using our proposed bonding metrics to verify whether users may bond more with a minimally designed accompanying robot when it follows a reactive or a proactive behavior mode.

## 6.3 Method

### 6.3.1 Interacting With ROBOMO

ROBOMO has a long shaped body utilizing an attractive container (made of plush material) and has no arms[2]. We intentionally gave ROBOMO a pitcher plant (Nepenthe) appearance to encourage people to interact with it, much as one might with a young child or a pet. We believe that exposing a half hairy head (Figure 6.1), makes the robot look cute and affords a starting point for the social bonding process formation. Although used for personal navigation, our accompanying mobile robot is unable to walk.

The human has to carry the robot just as we might carry a baby. In [184], Kemper et al found that touching a robot decreases the perceived machine-likeness of the robot and the human's feeling of dependability. This makes our robot more human-like and can be used as an indirect trigger for users to bond with ROBOMO. ROBOMO uses the IUs and Gs as two communication channels helping to generate different behaviors (indicate directions, confirmation or denial behaviors, happy and sad gestures or tones). Tones are generated based on Text-to-Mary Speech software that a markup language, can lead finally to the generation of a file that contains the speech with the emotion indicated in <emotion><category name="happy or sad"/>Speech </emotion>. If the category name is indicated the main program EmoSpeak related to Text-to-Mary speech will use 3 dimensions related to Mehrabian's PAD model with special coefficients for each descriptor related to the emotion in question. e.g: <dimension name="arousal" value="0.3"/><!–lower-than-average arousal–> <dimension name="pleasure" value="0.9"/><!–very high positive valence–> <dimension name="dominance" value="0.8"/><!–relatively high potency–>.

The IUs were produced according to the generation method for IU described by Okada et al.[129]. An IU can be defined as a porosodic component of speech that it is capable of transferring a meaning to the listener. As an example, one can cite the earcons (non verbal audio messages), the humming sound of a baby, etc. We used the hummed sound because it is proven in daily life that humans like a babies hummed sounds, may establish communication protocols using it and even memorize it. Two types of behaviors were exhibited: (i) the IUs:yes, no, right, left, back, forward, go, stop, slow down, happy or sad tones based on the user's guessing of the next direction and (ii) Gs: turn left, turn right, yes (to implicitly mean "go"), no (to implicitly mean "stop"), bow to the front, bow to the back, happy (small gesture of a dance) and sad (a sad posture while the robot's head bows down) gestures. A user has to ask the robot to give information about the direction (reactive mode). So, by reactive mode, we mean that the human has to emit the request and the robot will respond asynchronously

[2]ROBOMO's design was awarded in ICSR 2012

to that human's request. When the robot automatically helps the user without the human asking, it is called a proactive behavior.

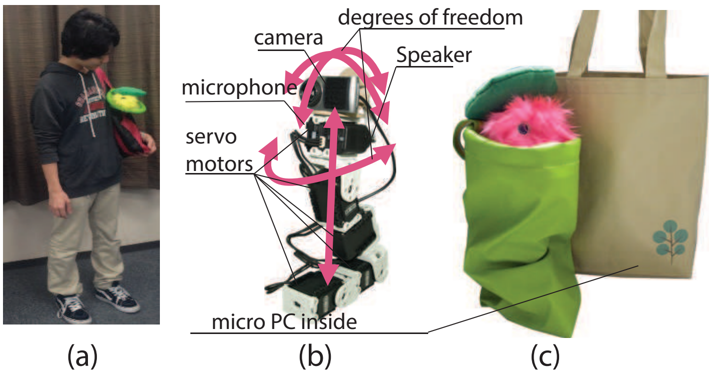



Fig. 6.1 A picture of our accompanying robot named ROBOMO.

### 6.3.2 Availability of our Research

The issue under scrutiny in this work is the design of four measures for the quantification of social bonding between humans and robots. If the four measures for the quantification of social bonding are validated we then may use them to test out whether a modification on the robot's design, by adding or taking out a behavior, may bring about better social bonding. In daily life, if the social bonding increases, the human's dedication and implication on society increases too [138]. By analogy to that, if the human's social bonding increases during the HRI, we have a positive HRR and we may say that a state of harmony governs the HRI.
A unique point regarding the current study, is that it is premised on the assumption that the four factors defining social bonding should be taken into account rather than only one factor being the attachment; that being the only element used to measure bonding and used in many previous HRI studies [162][164], etc. Another unique topic in our study concerns the fact that we want to measure the bonding between a robot and an adult rather than just focusing on the bonding that may evolve between a child and a robot for two reasons. The first reason is that, we think that adults have to test out the robot initially before feeling that it is safe and convenient for their children to use. Secondly, only a minority of social robots are conceived for usage by children and most of the HRI studies consider only adult users. So as a summary, it is very reasonable to consider the bonding between adults and children. Furthermore, most of the HRI studies that concern the accompanying robots focus on the achievement of the task and did not approach the problematic issues of social bonding. In addition to that, they focused on accompanying robots that integrate a large number of sensors and effectors. In our study, we focus on both task achievement and the social

bonding that may evolve between the user and the accompanying robot. Our accompanying robot is minimally designed to make it affordable, simple to use and to avoid any adaptation gap related to the robot using a very high number of sensors and effectors which may, in turn, increase people's expectations about the robot's functions. By elaborating on the nature of the minimalist robot, a human will have low expectations relating to the robot's functionality and may better tolerate the robot's eventual mistakes [75].
Finally, if our designed four measures for the quantification of social bonding are reliable, it would be interesting to present a case study where we use them for measuring the social bonding which evolves between a human and a robot if we add a new behavior. Thus, although there is overwhelming evidence corroborating the notion that a proactive robot is preferred over a reactive robot, it can be of paramount importance to test out the social bonding trend in both behavior mode cases (reactive and proactive) and choose the most appropriate mode.

### 6.3.3 Task and Experimental Procedure

Fig. 6.2 A user interacting with ROBOMO.

We setup an indoor ground for a navigation task (10mx6m) that contained many intersections (Figure 6.3). In each intersection, the participant should ask about the direction to be chosen. To pick the next direction, the participant is instructed by the robot. Users need

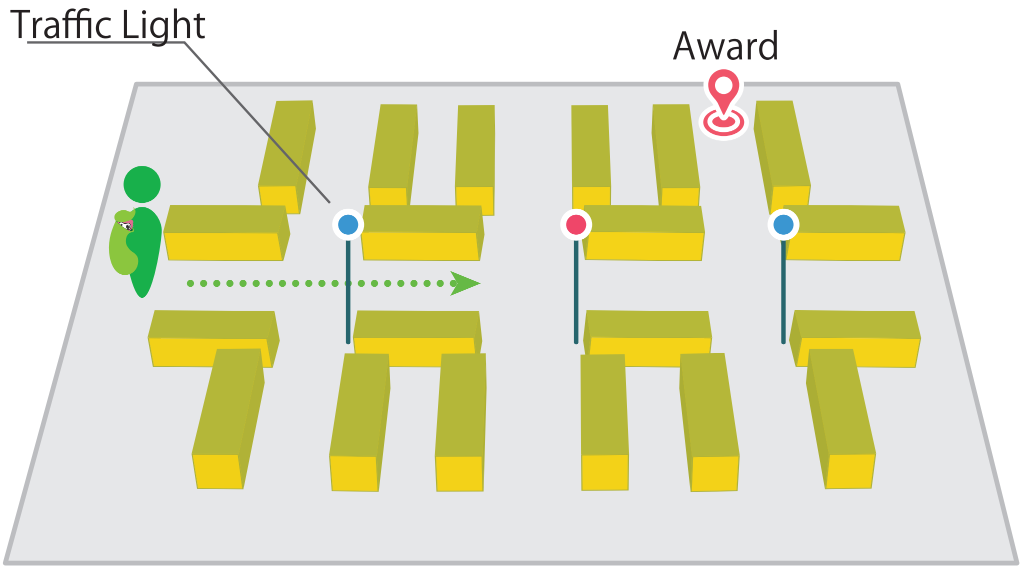



Fig. 6.3 The experimental setup: The human has to hold the robot and emits his request to ROBOMO.

to complete the task and reach the reward (music CD) location. They ignore the reward location and only rely on the robot's guidelines in order to complete the task. Thus, the general task was to follow the robot's instructions in order for the location of the reward to be reached. However, we designed the experiment using four different conditions[3]. When answering the human's request, in condition 1 (C1), the robot uses only IUs, in condition 2 (C2), the robot uses only gestures, in condition 3 (C3), the robot combines the IUs and the Gs in a reactive mode of behavior (a reactive mode of behavior corresponds to the robot only answering the user's requests without any anticipation of the human's demands) and in condition 4 (C4), the robot combines the IUs and the Gs in a proactive mode of behavior (a proactive mode of behavior corresponds to the robot taking the initiative and telling the user about the next direction without the user asking). 10 participants took part in each of the different conditions. In each condition, the participant interacted with ROBOMO for at least two minutes and then answered the questionnaires indicated in the section 6.3.4. Participants ages vary from $[22-30]$ years old (Figure 6.2). We told to each participant that they may ask the robot's again in cases where they did not get the robot's answer the first time. The whole experiment was video recorded so that the users' facial expressions[4] could be detected. We formed the first hypothesis (H1) regarding how combining numerous channels of communication may enhance social bonding while:

[3]By condition here we mean the way the robot will adopt to interact with the human
[4]Features used to determine the facial expressions are the lips, eyebrows, eyes

- H1: Participants who are taking part in the third condition show better social bonding and rate their experience with the robot as more positive than those who participate in conditions 1 or 2. This prediction follows the baby-caregiver schema and joins Belpaeme et al [160] insights. Belpaeme et al [160] suggested that using synchronized communication channels may bring about better social bonding.

If participants of condition 3 show better social bonding than those in conditions 1 and 2, we can validate our conceived social bonding measures and we can further use it for more difficult design choices in order to enhance bonding. Our second design choice concerns the comparison of conditions 3 and 4. Thus, hypothesis 2 can be formed as follows:

- H2: We expect that participants who take part in the condition 4 show better social bonding and rate their experience with the robot as more positive than those who participate in conditions 3.

### 6.3.4 Bond Metrics

To measure the social bonding we established, based on each of the bond's factors definition a set of subjective and objective metrics. We associated the belief factor[5] for the human's belief in the robot's social presence and it conscious agency. We then calculated the instances of eye contact (based on the recorded videos), the rate of respect[6], the number of averted gazes, and finally the cooperation metric (a 7 point Likert-scale questionnaire inspired from [129]).
As for the attachment factor[7], is the emotional link that may evolve during the HRI, we used 7 point Likert-scale metrics, one that included : the pleasure [185], the caring [110], the perceived closeness [129], the stress-free [129] and the likeability [108].
The commitment factor[8] involves time, energy and effort expressed in conventional lines of action to achieve the task goals. To measure this commitment, we measured cognitive effort using a 7-point Likert-scale with the following metrics: the arousal [185], the mutual attention, the users evaluation of the robot's "cognitive" effort through the perceived competence [110] and the perceived intelligence [108]. We also measured the user's: success-

[5]The actual questions related to the survey for the belief component are described in: http://goo.gl/forms/6DXgwH3poK

[6]Rate of respect=number of times the human asked the robot/number of total times the human should have asked the robot (a specific number for each configuration). This indirectly gives us an impression of the overall system's performance and the participants' ability to understand the feedback (intelligibility)

[7]The actual questions related to the survey for the attachment component are described in: http://goo.gl/forms/eoikVunVjG

[8]The actual questions related to the survey for the commitment component are described in: http://goo.gl/forms/ItqTMqKVpU

ful cognitive effort[9], expanded energy (physical effort rate[10]) and time (interaction time). Achievement was also measured (achievement [129]) just like Tanioka and Glaser [186] used achievement scores to measure the commitment factor in schools. Finally, we asked users to describe their experience with the robot (situational empathy[11]) just like Lasley et al. [187] used self-report descriptions of high school students to assess their evaluation of the attainment of good grades. In our case, the human subject was required to talk about the most prominent achievements that they believed the HRI succeeded in attaining.

The involvement factor[12], is closely tied to the commitment factor in that it entails the actual amount of extra expanded time a human takes to pursue the HRI. It is also an indicator of the human's adaptation according to Chris et al [188]. It focuses on the idle time available when one is not engaged and the effort expended during that extra time. We used 7-point Likert scale questionnaires to assess the involvement bond through different metrics: positive[13] and negative[14] human faces support [109]. We calculated based on the recorded videos, the number of times that eyes were wide open (surprised)[15], the corners of the mouth were turned upwards (disgust), one eye brow raised (wondering)[16] and mouth corners raised (happy) since these are optional behaviors that the human is not obligated to express and which indicates that they are emerged by (involved in) the HRI. These parameters are coded two times and then to eliminate confusion about the ambiguous situations another coder interfered to give his opinion (cohen's kappa reliability 0.72).

Finally, we conceived another extra measurement, that of harmony[17] (not an extra factor). In fact according to Hirschi's social bonding, if the person believes (belief) on the usability of the interaction with society, shows that they are indeed committed to social activities, appears attached to society and social events and finally proves that they may even afford extra energy to become highly involved in society (involvement), meaning that there will

[9]Successful cognitive effort= successful interactions/ total number of interactions. It indirectly gives us some idea about the overall system's performance and the participants' ability to understand the feedback (intelligibility)

[10]Physical effort rate=number of steps/ total number of due steps (a specific number for each configuration). It indirectly provides us with an idea of the overall system's performance itself and the participants' ability to understand the feedback (intelligibility)

[11]It is the human's empathic reactions in a specific condition

[12]The actual questions related to the survey of the involvement component are described in: http://goo.gl/forms/YUCtIVuNz0

[13]Positive Social face [188]: It includes one's desire to be included and appreciated during the interaction with others.

[14]Negative Social face [188]:It also includes one's desire that their interaction with others can be free from imposition and constraints so that they can feel free.

[15]The contour of the eyes becomes bigger but the eye brows do not move.

[16]The eyes contour does not change but one eye brow position changed.

[17]The actual questions related to the survey of the harmony are described in: http://goo.gl/forms/M7DWeM1mqO

be less chances that the person deviates or shows inadequate behaviors. By analogy to that, we designed a harmony factor that is related to one's overall acceptance and positive rating of the HRI. Harmony is articulated in three points which are the robot's persuasiveness, the user's level of trust on the robot and whether the human will use the robot on a long term basis or not. To measure persuasiveness, we instructed subjects to arrange a list of words according to their own priorities and then we calculated the level of persuasiveness using the Kendall-tau distance metric [189]. We also measure trust based on the questionnaire cited in [110] and the expected long-term use based on the questionnaire cited in [129].

In fact, by measuring the four different designed factors, we may be able to evaluate the social bonding level. By comparing the social bonding level with the harmony factor we can more sure about the social bonding results. In fact, if social bonding increases and the harmony results increase too, that means that we have reliable results about the bonding.

## 6.4 Results

### 6.4.1 Investigation of Hypothesis 1 [H1]:Social Bonding Evaluation in the Three First Conditions

We conducted ANOVA and Tukey-HSD tests to compare the bonding results of conditions 1, 2 and 3. We present in Table 6.1 the comparison results. Table 6.1 shows the Tukey-HSD results comparing conditions 1 and 3 (C1 vs C3), the comparison of conditions 1 and 2 (C1 vs C2) and the comparison of conditions 2 and 3 (C2 vs C3). We also indicate for each metric the percentage of users whose related bonding metrics' values increase in conditions 1, 2 or 3.

By comparing conditions 2 and 3, we remark that condition 3 affords higher social bonds metrics' values.

By comparing conditions 1 and 3 Tukey-HSD results (Table 6.1), we notice that there are statistically many differences between these two conditions except for some metrics which are: the successful cognitive effort and the number of times the user was disgusted or wondering.

This leads us to deduce that the IUs were sufficient to understand the interaction's context (no statistical differences for the metric successful cognitive effort). Consequently, if the human understands the interaction's context in condition 3 it is not dedicated to the presence of Gs, because the robot uses only IUs in condition 1 and we still have the same rates of successful cognitive effort[18] as in condition 3.

[18] As a reminder, it is the number of times a participant guesses what has the robot meant by his guidelines.

| Bond | Metric | F-test | P-value | C1 vs C3 | E | C2 vs C3 | E | C1 vs C2 | E |
|---|---|---|---|---|---|---|---|---|---|
| B | nb of eye contact | 272.065 | < 0.001 | < 0.001 | C3 (100%) | < 0.001 | C3 (100%) | < 0.001 | C1 (100%) |
| | rate of respect | 129.157 | < 0.001 | < 0.001 | C3 (100%) | 0.0052 | C3 (85%) | < 0.001 | C1 (100%) |
| | nb of averted gaze | 27.990 | < 0.001 | < 0.001 | C1 (15%) | 0.0006 | C2 (85%) | 0.2 | C2 (20%) |
| | cooperation | 127.733 | < 0.001 | < 0.001 | C3 (100%) | < 0.001 | C3 (90%) | < 0.001 | C1 (100%) |
| A | pleasure | 46.672 | < 0.001 | < 0.001 | C3 (90%) | 0.0003 | C3 (70%) | < 0.001 | C1 (100%) |
| | caring | 63.687 | < 0.001 | 0.0336 | C3 (100%) | < 0.001 | C3 (90%) | < 0.001 | C1 (100%) |
| | perceived closeness | 56.394 | < 0.001 | < 0.001 | C3 (100%) | 0.001 | C3 (90%) | < 0.001 | C1 (100%) |
| | stress-free | 106.935 | < 0.001 | < 0.001 | C3 (90%) | < 0.001 | C3 (95%) | < 0.001 | C1 (100%) |
| | likeability | 174.427 | < 0.001 | < 0.001 | C3 (90%) | < 0.001 | C3 (100%) | < 0.001 | C1 (100%) |
| C | arousal | 21.187 | < 0.001 | 0.019 | C3 (60%) | 0.001 | C3 (65%) | < 0.001 | C1 (80%) |
| | mutual attention | 46.046 | < 0.001 | < 0.001 | C3 (90%) | 0.001 | C3 (100%) | < 0.001 | C1 (100%) |
| | achievement | 23.267 | < 0.001 | < 0.001 | C3 (85%) | N/A | N/A | C1 < 0.001 | C1 (90%) |
| | perceived competence | 172.972 | < 0.001 | < 0.001 | C3 (100%) | 0.021 | C3 (70%) | < 0.001 | C1 (100%) |
| | perceived intelligence | 49.662 | < 0.001 | 0.024 | C3 (70%) | < 0.001 | C3(100%) | < 0.001 | C1 (100%) |
| | physical effort rate | 93.596 | < 0.001 | < 0.001 | C3 (100%) | < 0.001 | C3 (100%) | < 0.001 | C1 (100%) |
| | successful cognitive effort | 4.873 | 0.011 | 0.072 | N/A | 0.734 | N/A | 0.010 | C1 (70%) |
| | interaction time | 163.299 | < 0.001 | < 0.001 | C3 (100%) | 0.640 | N/A | < 0.001 | C1 (100%) |
| I | HPFS | 19.357 | < 0.001 | < 0.001 | C3 (100%) | 0.278 | N/A | < 0.001 | C1 (100%) |
| | HNFS | 12.980 | < 0.001 | < 0.001 | C3 (85%) | 0.500 | N/A | 0.001 | C1 (70%) |
| | adaptability | 70.999 | < 0.001 | < 0.001 | C3 (100%) | 0.843 | N/A | < 0.001 | C1 (100%) |
| | surprised | 14.672 | < 0.001 | 0.001 | C1 (10%) | 0.294 | N/A | < 0.001 | C1 (5%) |
| | disgusted | 1.815 | 0.172 | N/A | N/A | N/A | N/A | N/A | N/A |
| | wondering | 1.798 | 0.201 | N/A | N/A | N/A | N/A | N/A | N/A |
| | happy | 12.590 | < 0.001 | < 0.001 | C3 (80%) | 0.011 | C3 (30%) | N/A | N/A |
| H | trust | 35.417 | < 0.001 | < 0.001 | C3 (95%) | N/A | N/A | < 0.001 | C1 (95%) |
| | long term use | 26.826 | < 0.001 | < 0.001 | C3 (85%) | N/A | N/A | < 0.001 | C1 (100%) |
| | persuasiveness | 14.845 | < 0.001 | 0.001 | C3 (75%) | N/A | N/A | < 0.001 | C1 (80%) |

Table 6.1 The comparison results of C1, C2 and C3 (One way ANOVA and Tukey-HSD tests). E stands for the % of participants whose metric X (while X varies between number of eye contact to persuasiveness) results increase in C1, C2 or C3. N/A refers to cases when further statistical tests were not warranted (F-test is not significant).

Although users equally successfully guess the interaction's context meaning in conditions 1 and 3, participants seem to be happier in condition 3 and show the same level of some negative feelings (disgust, wondering).
As the social bonding increases mainly in condition 3, we expected that the harmony metric would increase too in that same condition (condition 3). That it is why, we compared the results of social bonding (the 4 different factors) with the harmony metric's results. Analyzed data show that, the robot is more persuasive, more trustworthy and thus people expect that they will use the robot on a long-term basis in condition 3 (Table 6.1).
Summing all up, we notice that by exclusively using only one of the behaviors (e.g using only the IUs or only the Gs and vice versa), the involvement bond does not show any amelioration (column 3 in Table 6.1) and as a result there are no statistical differences in the harmony results and the overall bonding in both conditions 1 and 2. We remarked also that IUs are easy to decode in condition 1 and that it is why there were no statistical differences concerning the cognitive effort put forward in order to achieve the task. So, if condition 3 succeeded on increasing social bonding as we have seen in Table6.1, it is because aesthetically it is better to combine communication channels and give the impression that there is a synchronization between the robot's speech and gestures [160]. Thus, we join Belpaeme et al [160] insights when they highlighted that a multimodal robot synchronizing communication channels may bring about better social bonding. This paves the way to us to validate our measurements of social bonding since they lend support to the same insights expressed in other HRI studies and encourage us to use these measures to evaluate the social bonding evolving in conditions 3 and 4 so that we can decide whether it is better to adopt the reactive or the proactive behavior mode for a minimally designed accompanying robot.

### 6.4.2 Investigation of Hypothesis 2 [H2]: Proactivity versus Reactivity

In this section, we compare the results of conditions 3 and 4. Table 6.2, shows the impaired two-tailed t-test comparison results of conditions 3 and 4. We call evolution (E) the percentage of participants whose given metric X (X varying from number of eye contact to persuasiveness) results, increase in conditions 3 or 4.
Based on Table 3, we notice that there is a statistically significant increase in the results of all the bonds except for some metrics. We remark that the number of averted gaze has no significant differences between both conditions (reactive and proactive conditions).
Also, we remark that there were no significant differences concerning the number of times the user was surprised. Finally, for the other three most redundant facial expressions (disgusted, wondering, happy), there were no special tendencies highlighting that one of the conditions led to significantly better results concerning these three facial expressions states.

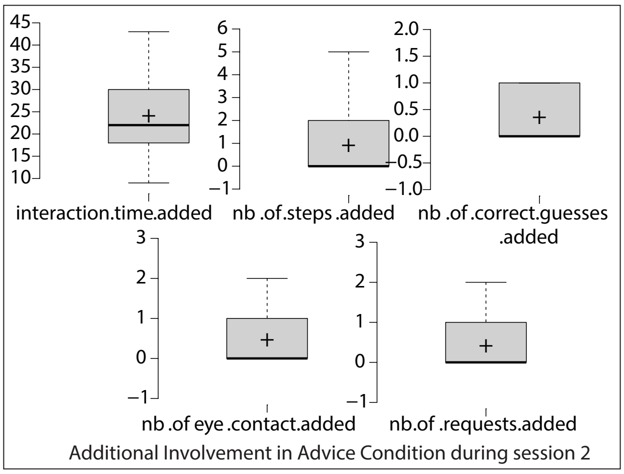



Fig. 6.4 Extra effort and time put forward by the user in C4.

Participants were able to add extra time, physical and cognitive effort during condition 4 (Figure 6.4) while barely finishing the task in condition 3. Figure 6.4 shows that, participants add extra interaction time in condition 4 which explains the increase in the number of requests, steps, correct guesses (guesses of the robot's generated IU's meaning), and the number of times the user made eye contact with the robot.
As the overall bonding was higher during condition 4, we expect that the harmony factor values will ameliorate as well in the same condition (condition 4). By examining the results of the harmony metric[19] we remark that, for both groups, there is a rise in the persuasiveness, trust and expected long-term use of the robot during condition 4. To summarize, these results highlight that for an accompanying minimalist designed robot like ROBOMO, a proactive mode is preferred over a reactive mode in terms of social bonding.

## 6.5 Discussion

### 6.5.1 Social Bonding Measures Validation

We tried to investigate whether we have higher bonding and as a result better harmony metric results when the robot uses the IUs, Gs or the combination of IUs and Gs. If we are able to use our conceived metrics and join Belapeme et al [160] in saying that broadly speaking a combination of communication channels is better for social bonding evolvement, we can then ensure that our tool measuring the bonding in a more standard way (just like Hirschi described in [159]) is reliable and we can use it for further difficult design decisions. As an

[19] It helps to give an idea about the tendency evolvement of the human robot relationship.

Table 6.2 The comparison results of C3 and C4 (2 tailed impaired two-tailed t-test, df=19, alpha=0.05: proactivity versus reactivity). E stands for the % of participants whose metric X (X varying from nb of eye contact to persuasiveness) results increase in C3 or C4. N/A refers to cases when further statistical tests were not warranted (t-test is not significant).

| Bond | Metric | T-test | P-value | E |
|---|---|---|---|---|
| B | nb of eye contact | 6.321 | < 0.001 | C4 (75%) |
| | rate of respect | 4.004 | < 0.001 | C4 (70%) |
| | nb of averted gaze | 0.115 | 0.909 | N/A |
| | cooperation | 2.257 | 0.03 | C4 (50%) |
| A | pleasure | 5.12107 | < 0.001 | C4 (85%) |
| | caring | 5.976 | < 0.001 | C4 (95%) |
| | perceived closeness | 3.707 | 0.001 | C4 (80%) |
| | stress-free | 9.612 | < 0.001 | C4 (100%) |
| | likeability | 5.881 | < 0.001 | C4 (85%) |
| C | arousal | 7.922 | <0.001 | C4 (100%) |
| | mutual attention | 2.123 | 0.04 | C4 (60%) |
| | achievement | 2.081 | 0.044 | C4 (65%) |
| | perceived competence | 2.26 | 0.03 | C4 (80%) |
| | perceived intelligence | 5.984 | <0.001 | C4 (95%) |
| | physical effort rate | 2.879 | 0.007 | C4 (95%) |
| | successful cognitive effort | 9.126 | <0.001 | C4 (100%) |
| | interaction time | 4.389 | < 0.001 | C4 (100%) |
| I | HPFS | 3.733 | 0.001 | C4 (100%) |
| | HNFS | 3.715 | 0.001 | C4 (75%) |
| | adaptability | 9.185 | <0.001 | C4 (100%) |
| | surprised | 0.551 | 0.585 | N/A |
| | disgusted | 0.2 | 0.515 | N/A |
| | wondering | 0.811 | 0.422 | N/A |
| | happy | 0.571 | 0.572 | N/A |
| H | trust | 2.633 | 0.012 | C4 (70%) |
| | long term use | 2.796 | 0.008 | C4 (65%) |
| | persuasiveness | 2.125 | 0.04 | C4 (65%) |

example, deciding whether a minimally designed accompanying robot should be reactive or proactive. Referring to Table 6.1, we remarked that IUs are enough to guarantee the user's understandability of the interaction. That it is why there were no statistically significant differences between conditions 1 and 3 in terms of successful cognitive effort. We remarked also by comparing conditions 1 and 2 in that, because involvement bond did not evolve, there was no amelioration in the harmony metrics indicating that in both conditions (1 and 2), the user evolves the same involvement when we use the IUs or the Gs. However, when we combine the Gs with the IUs, we notice that, the involvement increases significantly indicating that users were more engaged in the interaction. These insights are in line with Belpaeme et al [160] insights when they highlight that combining multiple types of communication strategies have a strong positive effect on the HRI. Belpaeme et al [160], used gestures and eye-gaze while in our current research, we use other alternative communication channels (IUs and Gs).
Therefore, taken together, our findings suggest that Belpaeme et al [160] insights can be extended to the case when the robot uses simply the IUs (rather than speech) and the Gs as powerful channels that have a strong effect on the HRI in terms of bonding evolvement. Consequently, one can validate and summarize hypothesis H1 as follows: Based on the four factors measuring the social bonding, combining IUs with Gs is better to evolve higher social bonding. This insight is in line with Belpaeme et al [160] insights which makes our measures reliable and encourages us to use them to decide whether it is better to adopt a proactive or a reactive robot.

### 6.5.2 Social Bonding Measures Promote the Proactive Behavior Mode

Based on the results exhibited in Table 6.2, we remark that participants have higher social bonding evolvement in the proactive condition in comparison to the reactive condition. There were some exceptions, while for example we notice that, the number of times the human makes an averted gaze to the robot is higher in condition 3 which means that the human's belief on the usefulness of the communication with the robot is inferior during condition 3. Furthermore, we notice that a user's facial expressions are not synchronized with the user's internal mood. In fact, although participants attributed higher pleasure results in condition 4, they were concentrating on the task achievement and so they had not the reflex to exhibit neither negative nor positive facial expressions. As a result to the increase of the factors in condition 4, harmony metrics values rise too during condition 4 indicating that, we have more social bonding when the robot starts to be proactive.
One important reason behind people preferring the proactive behavior is the reciprocity social law. Reciprocity is defined as the obligation to return in kind what another has done for

us. In fact, if the robot affords a service proactively to the human, we expect that the human will also afford high subjective ratings to the robot that can be longer interaction time because they enjoyed the interaction, tolerance of the robot's errors because it was adaptive to the human's requests and could propose help before that the human asks for it, etc. Folk wisdom recognizes reciprocity with such sayings as "You scratch my back and I'll scratch yours". The reciprocity norm is so powerful that it even applies to situations in which you do not ask for the favor [190]. So, participants had an acute sense of fairness when they are receiving help from the robot and they reciprocate that help indirectly by over benefiting the robot with higher social bonding ratings through the questionnaires results in the proactive mode because the robot was proactive when it offered the help.

## 6.6 Conclusion

We proposed four measures for the quantification of social bonding between humans and robots. We used these measures to assess social bonding in the presence of verbal and gestural interactions in 'proactive' and 'reactive' versions of a minimally designed accompanying robot called ROBOMO. The approach aims to measure four factors which are: 'belief', 'attachment', 'commitment' and 'involvement'. For that, we compared the social bonding values in the following different conditions: 'robot using only gestures', 'robot using only verbal behaviors', 'robot combining gestural and verbal behaviors'. We showed that combining verbal and gestural behaviors increased the user's preference of the robot and thus social bonding. Our proposed metrics were also used for the social bonding assessment when we decide to add proactive or reactive behaviors. Based on the results, we show that in the context of a minimally designed accompanying robot, a proactive mode adopted by the robot is preferred over a reactive mode. In fact, it leads to an amelioration of the social bonding.

Now, we studied the case when positive emotions may emerge and lead to social bonding. A long-standing stereotype held that emotions undermine rational thinking and make people do convenient choices such as interacting with others and enjoy the communication. However, psychological studies have shown that people who lack emotions (often because of brain injuries or other problems) are not really better off. They have great difficulty adjusting to life and making decisions. That is why, some people are not qualified enough to have the social bonding emerging. For such people, when service breakdowns would occur, taking a decision of continuing with the the minimally designed robot or move to another task would be difficult and lead to what we call cognitive conflict. In our next chapter, we entame a new experiment that may help us to find out a way to make these people who cannot evolve emotions take decisions quickly by making the robot propose a persuasive strategy to convince them continuing the interaction with the robot.

# Chapter 7

# TU/e Research

## 7.1 Abstract

Previously, we highlighted that some people do not evolve social bonding because they cannot have any kind of emotions when interacting with others. We call them utilitarian people. We clarified previously that in order that people could remember the rules of the PECP, they need to feel social bonding so that they cooperate with the robot during the HRI. However, for utilitarian people there a big chance that this kind of bonding does not emerge. Thus, the rules could not be encoded in the utilitarian user's mind. That it is why, we need to find out way that may convince them continuing the interaction with the robot even if the HRI encounters some breakdowns.

If we assume that initially the non-expert trainer (whatever is his profile: utilitarian or relational[1]) holds some preconceptions about the PECP and which are defeated by the robot behaving in a different way than expected, such a human may experience a cognitive conflict because of the difference of what it is expected and what it is perceived. We call such cognitive conflict, a cognitive dissonance.

This study investigated how social robots might use a persuasive technique after the no-expert trainer is stricken by the cognitive dissonance. When cognitive dissonance governs the situation, the human might want to overcome this dilemma by resuming the interaction with the robot or by abandoning the robot. We propose to apply a persuasive speech technique in an educational context, when the robot has to accompany a student that it is preparing himself for an exam. The insights that we might get, will have important implications for the educational use of robots, particularly for understanding of whether robots can positively affect learning through behavior change. The results of this study also contribute

[1] emotional

to our understanding of the extent to which the findings from social psychology got in real world between humans may carry over into contexts of human-robot interaction.
Furthermore, the timing choice to expose the persuasive message for this context of the study contributes to robot design by providing a new concept that it is the "gamma window"[2] related to how can we take advantage from aspects of the cognitive dissonance to obtain increased student's productivity and avoid the learned helplessness in the context of science learning by introducing the persuasive content during the "gamma window". This investigation was contextualized in science learning and, therefore, required gaining a better understanding of the student's learning science main struggles, the cognitive dissonance and the persuasive techniques that can be used in this context and which we will detail more in the coming sections.

## 7.2 Introduction

The field of social robots has grown into an extensive body of literature over the past years, with a wide variety of approaches for extracting human patterns and modeling robots' skills. Robots operate as partners, peers or assistants in a range of tasks such as with autistic children [191] [192], at homes [193], in hospitals [194] or for having fun; e.g: SONY Rolly [195], or the robotic toys from Wowwee [196], etc.. However, to be safely engaged during the human-robot interaction the robot has to exhibit it potential to influence the human's beliefs and attitudes at least to guarantee the human's trust about it usefulness. An attempt to change attitudes or behaviors or both corresponds to the definition of persuasion [197].
Many studies from HRI tackled the fact of how to afford the robot with the ability to persuade people in many application fields such as at school [198] , as story-tellers [199], or as inciters to conserve energy [200], etc.. For this purpose different points were investigated such as the effect of the robot's perceived gender on the robot's persuasiveness potential [201], the impact of using different types of social feedbacks (evaluative, factual, ambient, subliminal or supraliminal) on the robot's persuasiveness [200], the effect of the message source's physical appearance (picture, text message, video) on its persuasiveness [202], etc..
However, to the best of our knowledge no concern was paid to the serious conflicts that students encounter at schools while learning science (e.g: Mathematics, Physics, Chemistry, etc..) and the social robot key persuasive role that can be played in such a case.
Based on Abramason et al [203], these conflicts may lead to an objective non contingency while nothing the student does makes a difference to what happens, then a perceived non

[2] A period of time that starts after the human perceives that a cognitive dissonance occurs and the time when he finally take a decision to continue the interaction with the robot or to abandon it.

contingency where the student notices that nothing he does makes a difference, after that a negative attribution is formed where the non contingency is attributed to internal, global and stable factors, more expectations of non contingency are created where the student imagines that future tentative will make no difference to what happens and finally learned helplessness symptoms can be recognized based on the student's behavior when he has to resolve a science exercise. In such case, the student may experience a depression coupled with motivational deficits and with time he/she will avoid to resolve any science exercise.

According to the MODE model which is a model of attitude-behavior relation in which motivation and opportunity are necessary to make a determinant behavior, a lack in motivation or opportunity may activate attitudes that are highly accessible and those attitudes will activate their correspondent spontaneous behaviors.

In such a case, many parameters play key role to determine whether the student will be choking under pressure by using his pre-established negative highly accessible attitude (avoiding to redo the difficult exercise that led to the failure) or will keep an intrinsic motivation (be redoing the difficult exercise with a pure desire to strive to success) to ameliorate his understanding of the science exercise by accessing to his pre-established positive highly accessible attitude (consisting of defeating the science exercise if we suppose that the student is a defeater by nature).

In this context, the choice of the highly accessible attitude can be guessed through the student's habits. An emotional student that takes decisions in general based on his emotions and who is experiencing in addition to that the learned helplessness may avoid science learning and starts to elaborate a phobia from science. An utilitarian (cold-hearted) student that takes a decision based on reasonable thinking can strive to understand the science content rather than avoid it and still some other factors that can increase the possibility that he may avoid to redo the task as well. In fact, utilitarian people have high self esteem. High self-esteem people have positive illusions that may help them in their life but also that may cause perception perturbation and a high self-esteem that may make the student diminish the problem's magnitude and avoids in a twisted manner to answer the science exercise while pretending to be "not in the mood" for example.

Based on the theory of Planned behavior if we consider that the student will plan his future behavior rather than that it will be inferred spontaneously once he encounters a difficult science exercise, one can already know that no positive attitude will be activated when a cognitive conflict occurs because there will be weak perceived behavioral control since the student does not believe that he can perform (one of the symptoms of the learned helplessness) a relevant positive behavior (by redoing the science exercise). In fact, in order that a strong positive behavioral intention (which determine whether a positive behavior is activated or not) can be formed we need to have strong perceived behavioral control which is in this context inhibited because of the learned helplessness symptoms that stricke the student once he/she experiences the cognitive dissonance. Consequently, it is important to give a serious attention to the issue of the dangerous consequences of cognitive dissonance while learning science for both types of students (utilitarian and relational students). We need to grant the social robot with the ability to follow closely the student's engagement and employ persuasive strategies that may decrease the cognitive conflict which students may get through while learning science.

In our study, we intend to use a speech-based persuasive strategy inspired from social psychology, which was not experimented yet in the HRI studies combined with the factual and social feedback of an entity. This entity could be an embodied (box), an anthropomorphic minimally designed entity (such as a minimally designed robot), a human or nothing at all (baseline condition). We expect that such a combination of feedback may persuade the student and help with time to establish positive counter attitudes which if highly accessed it may help to predict the student's future behavior once he faces the same situation even if the persuader (the entity) is not there.

With such a setup, the human in the case of SDT for example will not have to feel the social bonding but have to evolve a new attitude implicitly thanks to the non deliberative persuasive technique proposed by SDT during the gamma window. If highly accessible, this new attitude can become a stable attitude in the human's cognitive miser (whatever is his profile). Even if the HRI encounters some breakdowns, the human will pay more attention to the robot and will not abandon it even if some breakdowns are encountered once an implicit new attitude emerged and which consists on resuming the interaction with the robot.

As for the speech-based persuasive strategy, we expose a wide range of different techniques such as : "foot-in-the-door technique", "labeling technique", "door-in-the-face-technique", "that's not all technique", "disrupt then reframe" while in our study for experiment design purposes related to the power analysis, we will consider only one persuasive message technique that it is "that's not all technique"

As for persuasive message sources, we consider a factual feedback message source represented by a tablet (presenting persuasive text), an anthropomorphic minimally designed social agent which is a robot called ROBOMO. Finally as another persuasive message source, we consider including in our study a human as a persuasive message source that also combines the speech based persuasive technique with a high level of social feedback.

# 7.3 Background

## 7.3.1 Cognitive Dissonance

There are many terms that were proposed with similar meanings to cognitive conflict such as cognitive gap [204], conceptual conflict [205] but also cognitive dissonance [206]. Cognitive dissonance is a discomfort that one in general experiences when an individual holds beliefs, attitudes or behaviors that are at odds with one another (the ratio between dissonant and consonant facts).

In [207], Douglas et all, confirm that to measure cognitive dissonance, we need to focus on three components which are the cognitive, emotional and behavioral components (Figure 7.1).

The cognitive component is related to the human's belief about the inconsistency after the decision is made (figure 7.1). Once the situation is evaluated, it leads directly to a bad emotional reaction. After some time elapses or what we call the gamma window (a period between the decision taking and the new action that should bring about more consistency) during which the human experiences an extensive causal analysis because of the new situation high distinctiveness, low consensus and low consistency [3], the counter attitudinal action is determined and that it is the behavioral component (figure 7.1).

In fact, after, introspection the human will take a counter attitudinal behavior based on the heuristics and the stereotypes that he believes he holds. Three different counter attitudinal behaviors are possible:

- An active attitude change (rationalization) with a new heuristic created. If that heuristic is brought to mind many times (the accessibility increases), it can be an essential element on the cognitive miser and it can help the human to strive to a better private and public self. The access to that heuristic depends of a simple tradeoff between accuracy (reliability) and speed (simplicity) (A).
- Minimize the importance of the cognitive dissonance (belief change) (B).
- Get new information to support his previous decision (perception change) (C).

Now, interestingly, when the student is experiencing a mixture of negative emotional state and cognitive dilemma, it is obvious that somehow the cognitive abilities will be used more and more to shut down as soon as possible the inconsistency alarm anyhow are the

[3] Consensus, distinctiveness and consistency are the attribution cube components which may define whether people will attribute a situation to internal, external causes or will arouse the person's curiosity to do an extensive causal analysis before taking the decision

costs. That it is why, an enlightening swift persuasive technique with some arguments during gamma window may empower the student to make an easy shortcut, reduce the cognitive workload and follow what the message given guidelines rather than putting a lot of effort to find out a convenient counter attitudinal behavior. Informational Influence here may play a key role while the student is choking under the stress (during the gamma window) (Figure 7.1).

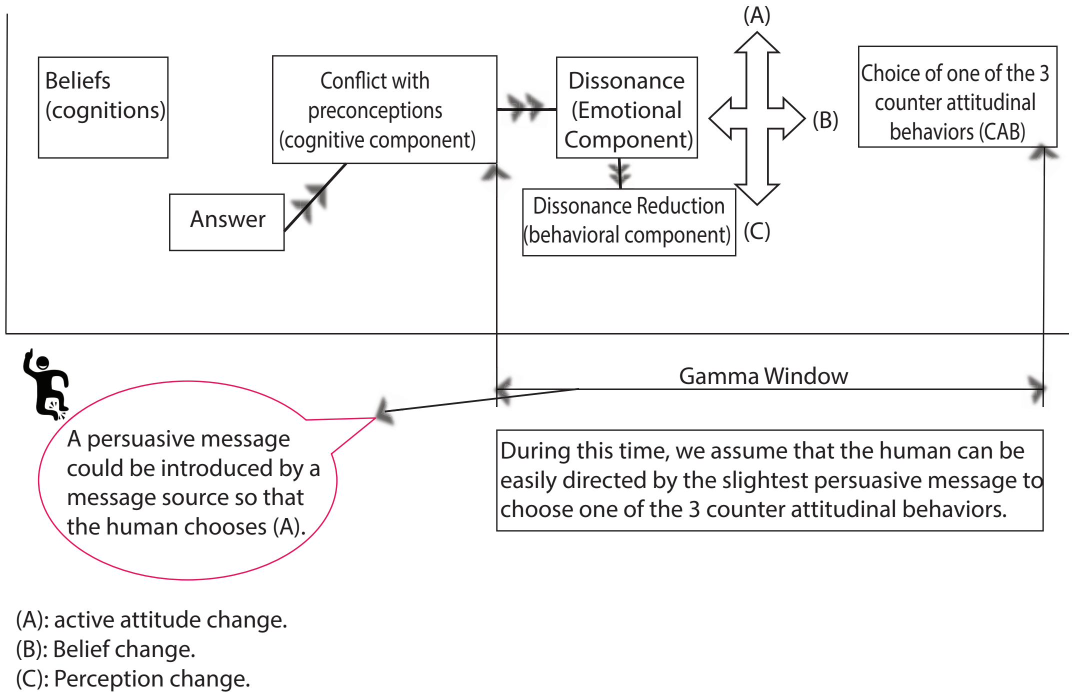



Fig. 7.1 Temporal relations among dissonance concepts.

### 7.3.2 Cognitive Dissonance Related Factors

Interestingly, there are a lot of factors that may determine whether a person may experience a cognitive dissonance or not. According to the situation some people may not feel cognitive dissonance because of different factors. In fact, to be stricken by the cognitive dissonance, we need to have the luxury of "free choice situation" so that we can feel the responsibility against any damage and avoid any automatic egotism emergence. We must also avoid the shortcut of "I cannot anticipate the results" so the consequences should be foreseeable. The human should be aroused and he must strive for consistency motive even if the phenomenal self appears weak under the pressure of the cognitive dissonance situation.
Another point is that, the human must evaluate seriously the situation as his "private and

public self" are at risk and avoid making any false consensus [4] , self serving bias, illusionary correlation, etc. The cognitive dissonance can be of a great magnitude if there is a vested interest in the current faced situation that led to the cognitive conflict because things gain in value in our mind-set when they touch the self (endowment effect).

### 7.3.3 Persuasive techniques

There are a lot of speech based persuasive techniques that may empower the persuasive message.

#### Foot-in-the-Door Technique: (Going gradually from small to big requests)

It consists on starting a small request to get a larger compliance with a larger request. Complying with small requests seems like no big deal but it increases the possibility of complying with larger requests later on. If the increment in compliance requests is gradual then the request may seem like a small request. The main idea is that once people had committed themselves with a small request, they feel obligated to continue behaving consistently.

#### Labeling Technique: (A vivid message that sticks a positive label on your public self)

It involves assigning a label to the individual and then requests a favor that it is consistent with the label. For example telling to a student: I know you are striving to success and deep inside you are a hard worker. In such a case, the student has more tendency to live up with the positive label. Thus, one way to make a human produces the desired behavior is to assign positive label to him/her so that you can drive him/her to live up with that label and maintain that positive consistency which serves the public image of the person as well as his/her self-esteem.

#### Door-in-the-Face-Technique: (If not a huge advantage then what about a small one)

Here, we need to start by an inflated request and then retreat to a smaller request. After the first request is rejected the human will feel that he needs to change his opinion since the initial request has changed (a matter of reciprocity).

[4] False consensus effect: I believe that all people would do the same thing if they were in my place.

**That's not all-Technique (framed positively): (Incrementally, we give different positive arguments: slow speech speed with strong arguments)**

Here, we need to present a positive framed message while we give arguments incrementally in a way that we embellish our request each time by a new positive request so that we increase the person's engagement. E.g: tell for a student that according to Harvard's table of calories burned during different activities, concentrating during 30 minutes helps on burning from 53 to 78 calories which is an easy task and we got already the opportunity...That's not all you will increase also the neurons number and you increase your brain plasticity.. And guess what, that's not all.. once you finish this exercise we may say that you achieved the level 2 of this lesson.

**That's not all-Technique (framed negatively): (Incrementally give different negative arguments that may increase the fear: slow speech speed with strong arguments)**

Here, we need to present a negative framed message while we give negative arguments incrementally. Nobody can deny the magic of fear how it is useful to go through an exceptional experience of different unknown multiple emotions. So introducing a bit of fear in the persuasive message can help to make the student for example more aroused and focusing; of course with the condition that we afford some small reward to erase the fear effect. However, we have to be careful to maintain the intrinsic motivation of the student because once the student ties the reward to the science study task, the motivation will be extrinsic and he/she will no more does his/her science exercises unless she/he gets a reward.

**Disrupt-and-Reframe Technique: (Disrupt with humor and give only few arguments with fast speech speed)**

A momentary component is introduced in order to disrupt one's attention. That component can absorb critical thinking and prevents individuals from processing information. In fact, the main idea here is that when people are focusing a lot on some matter they are a bit difficult to be persuaded and it is better to guide them to use the peripheral route for arguments evaluation. As an example, if we tell to the student a small joke and then we ask him to go back to the exercise, he might comply.

In our work we will be using only one method that it is "that's not all technique positively framed" for purposes related to the experiment's design (power analysis). We intend to consider the other techniques in a future work.

### 7.3.4 Persuasive Methods Related Factors

There are lots of factors related to the persuasiveness as well as many strategies that can be used to persuade people in general to make a "healthy" introspection and make the "right" choice once enlighten by a persuasive message.
We may give a small list of those factors as follows:

**Normative Influence (Pathos and Etheos)**

The fact to be liked gives you the power to easily influence. So, we must measure the likeability of the persuader.

**Intellectual Appeal (Logos)**

It mainly concerns the fact whether people think that the persuader has a deep knowledge and he makes usage of analytical methods so it is interesting to measure the perceived expertise of the persuader.

**Credibility**

We have always that urge to feel that the message is coming from an honest source. But, somehow if the arguments are persuading, people may detach the message from the source (what we call the sleeper effect). Thus, measuring credibility is always a good option because people may determine unfortunately in delayed time whether the message was persuading with great arguments or not so that they can detach it if the persuasive message source was not credible.

**Need for Cognition**

Here we need to focus on whether the audience needs cognition (strong arguments) or it is not that important (weak arguments may suffice).

**Concern About Public Image**

It is not obvious that all people are seeking to work on their public self because there are some self esteem seekers that can even sacrifice their partners just to increase their self-esteem.

### Age

It is not easier to make people between 34 and 83 change their opinions while it is easy to do so for young adults, children and adolescents. So, to avoid a biased sample and to guarantee the ecological validity, it is better to think of taking participants of different ages (e.g: In our case, we talk about students so it is better to consider students of all ages.). For purposes related to the power analysis, we cannot consider a wide range of age. That it is why, a generalization is possible when we conduct more studies with students from many ranges of age.

### Gender

There are some assumptions that females are easier to be persuaded.

### Source of attractiveness

This is a quiet tricky way to transfer your persuasive message. You just need some subtle cues when a distracting source is there because in that time you are calling upon the automatic processing of information of people rather than their conscious processing system (peripheral route).

### Personal Relevance

When affording a persuasive message, it is better to think about including something that it is relevant to the audience.

### Initial attitude

If the initial attitude is strong, changing the audience mind can be a bit difficult.

### Sufficient Prior knowledge

We need to have a minimum of knowledge when we are in a conflicting situation so that we can judge what it is good and what it is bad. In our study, we need to measure these different factors to determine the different persuasive message source influence on students.

### 7.3.5 Factors Related to the Application area

Based on [198], [208] and [209], different other independent variables that can be considered to study the students' reactions while learning science. The independent variables which can be considered in our case are:

#### Prior knowledge

whether the student has some prior knowledge about the learned subject.

#### Cognitive Closure

whether the student's looks for consistency.

#### Motivation and interests

whether the student is motivated to learn science in general.

#### Evaluation of the participants' perception of the robot (related to attribution theory: thoughts listing task):

Attitudes can be measured through free-answers explicitly. The information gained from the student's explicit answers helps to gain an idea about how student may take the decision when they have to decide about deliberate information.

## 7.4 Study's Relevance and Hypothesis

Based on previous studies, we have afforded a framework helping to enable robots with the capability of building in an adaptive way communication protocols. The main problem was that users forget their previously established communication protocols (PECP) and the HRI during a new interaction's instance may encounter many breakdowns that need to be gracefully mitigated so that the non-expert trainer does not feel bored or that he thinks that the robot is useless and he continues the dynamic scaffolding or at least the PECP reuse. That it is why, we focused on the usage of IUs combined with the robot's visible behaviors synchronously so that the human could form implicitly some audio icons on his mind to remember the PECP when it has to be used.
During the first HRI instance there will be the encoding of the communication rules using the IUs as audio icons while in the second interaction instance, there will be a recall of the PECP using these same IUs. In such a way, the users social faces will not be threatened by

a defeating speech saying that they are wrong while reusing the PECP. Also, they will be implicitly more aware next time that they need to remember the PECP and IUs may help them to memorize the rules. However, to be able to cooperate to such a level there must be a minimum of positive emotions or what we call social bonding felt by the human towards the robot. That it is why, we conceived our tool helping to measure the social bonding and we used it in a case study to conclude that proactive minimally designed robots may trigger more social bonding formation when IUs are synchronized with the robot's visible behaviors.

However, to feel positive emotions the human has to evolve some empathy or at least we may say that the human must be not cold-hearted because cold-hearted or what we call in our manuscript utilitarian people, do not feel emotions so that they could implicitly form such rules of interaction. Consequently, we need a method that may help us to convince such utilitarian people to continue the interaction with the robot even if some breakdowns occur. In the previous paragraphs, we assumed that if a persuasive message spoken by a persuasive source during gamma window, we could better convince people to continue reusing the robot.

So the research question H1 of the first experiment (H1E1): "consists on *comparing the persuasiveness effect when a persuasive message is spoken "during gamma window", "after gamma window", "before gamma window" and a baseline condition when "no persuasive message is proposed by the persuasive source"*. In this experiment, we have the robot as the persuasive source that will generate the persuasive message. The technique that will be considered is the "that's not all technique" and there are different variables (independent and dependent) that will be measured in order to make the comparison which we explain more in section 7.7.

In our second experiment, we have not made the differentiation between relational and utilitarian people and we decided to consider both profile types to conduct a comparison between both types. In fact, even relational people could sometimes deviate. We explained previously that sometimes the human's behavior is spontaneous and triggered by the automatic processing system of the human. For each behavior, there is an activating stored attitude in the human's cognitive miser. We do not know whether the human's behavior when a breakdown is encountered will be activated by the automatic processing system (spontaneous behavior) or will be a planned behavior while the human will be fully aware and would call upon his positive emotions to cooperate with the robot during the interaction and using the IUs. So, if accidentally the relational person has a negative attitude stored in the cognitive miser and acts sometimes spontaneously, he may stop at least sometimes the interaction with the robot which will not help to achieve the task and may cause on long-term to distort

the relationship between the human and the robot.
Consequently, in our first hypothesis of the second experiment*(H1E2): We expect that the more a participant scores high on the dimension of relational (vs utili), the more that participant will be persuaded since we assume that they are more cooperative than utilitarian participants.*. Here, we have three different persuasive sources ("a gadget in a box", "the robot", "a human") as well as a baseline condition where there is no persuasive source. In our second hypothesis of the second experiment *(H2E2): We expect a main effect of persuader social agency type. That is, we expect that when a participant interacts with a gadget in a box, he or she will be persuaded less than when that participant interacts with a robot, in which situation the participant will be persuaded less than when that participant will interact with a human and of course having a persuasive source is better than nothing.*
Finally, in our third research hypothesis of the second experiment*(H3E2): We expect, most importantly, an interaction between the manipulation of persuader social agency and persuaded relational-utilitarian type. We are interested in whether the persuader's agency is equally effective for utilitarian and relational people (it is the change in the simple main effect of persuader's agency over levels of profile: 2 levels (utilitarian and relational)). That is, for people who are relational, they are more prone to follow equally the human or the robot's persuasive message rather than the box's persuasive message and overcome the cognitive dissonance. In contract, for people who are utilitarian, the effect of the persuasive message is of the same magnitude independently from the message's source but the presence of a persuasive message is better than the condition when there is no persuasive message (when the utilitarian human is left alone to face the cognitive dissonance).*

## 7.5 Setup

Participants are first given a brief description of the experiment procedure. After the introduction, they were asked to answer a pre-experiment survey (section ). The instructor will then demand from the student to enter to a room. After the participant is seated, the instructor will demand from the student to pay attention to the main screen placed in front of the student. He has to start resolving the science exercises (physics, mathematics, algorithmics exercises). The graphical interface has two blocks. One that it is reserved to the current exercise which the student needs to answer and another one that it is related to the next exercise. In the first block, we have also a text area where the student can write his analytical answer. In block 1, we have also a text area dedicated to the numerical answer. Once the student is sure from here answer, he has to click on the bottom submit. If the answer was correct the score will be 10. If the numerical answer was incorrect and the analytical answer quotes

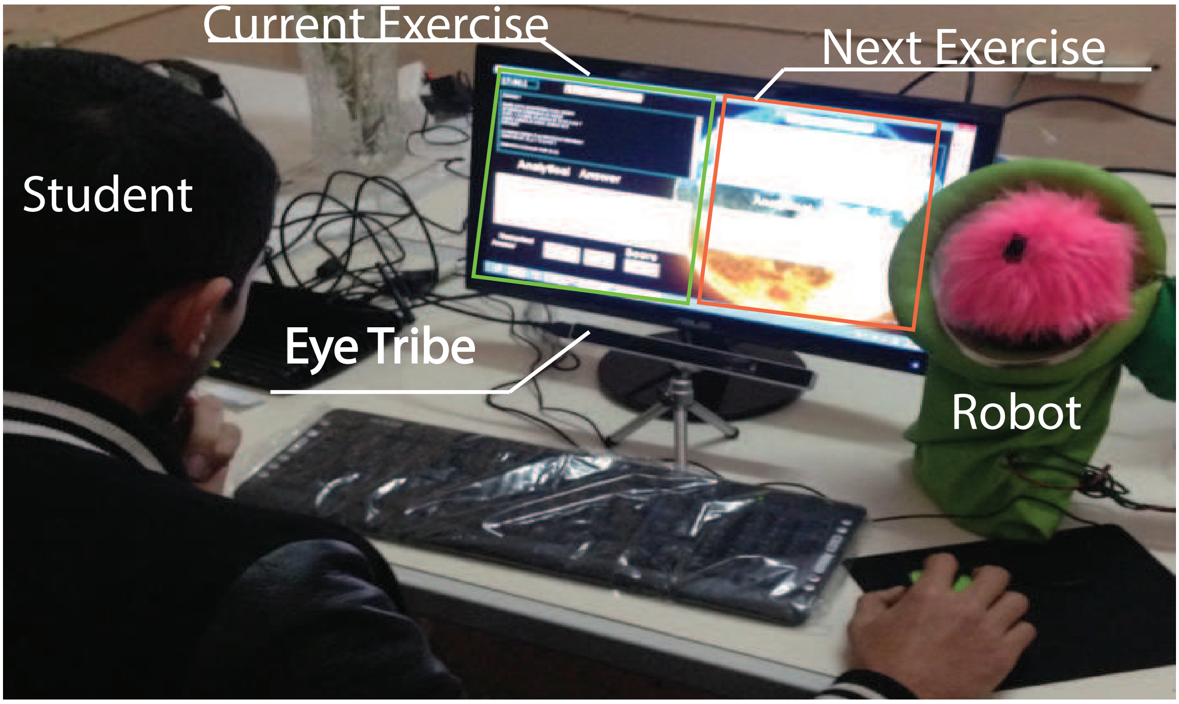



Fig. 7.2 The general setup of the experiment.

correct the student will have 5. If the student's answer was incorrect he has two options: whether redoing the current exercise or moving to the next exercise. To make sure that the next exercise easiness will not influence the student's choice (without you redo the current exercise or not) we managed to make the next exercise's picture fuzzy. Consequently, the student one striking by his incorrect answer he has to face the situation without being influenced by the exercises. Here the student can choose to jump to the next exercise. In such a case the student is making a belief change (B). If the student chooses to redo the current incorrect exercise he is engaging himself in an active attitude change (A). However if the student redoes weed and feed yourself no delete the exercise while not changing his answer in comparison to the previous answer, we might say that the student is making a perception change (C). To assess in real time the student's cognitive process replacing an eye tribe in parallel to the graphical interface displaying the exercises. The eye tribe helps to track the student's eye movement in real time. We managed as well to add a mouse listener to the interface so that we can detect the user's choices process before making the final decision (whether to do the next exercise or to stay who is the current exercise).

We had students from three levels: second, third and fourth grade. For each level there are three different options: Doing a mathematical exercises serie or doing an algorithmic exercises serie or doing physics exercises serie. In fact, by asking teachers we noted that

students whose main speciality is mathematics, do not like algorithmic exercises. So, when we gather a student whose main speciality is mathematics, we assigned for him an algorithmic exercise to be sure that he will be striken by the cognitive dissonance. Another example could be students whose speciality is algorithmics. These students do not like physics exercises. That is why, we manage to assign for these students only physics exercises so that they can experience the cognitive dissonance.
Each exercises' collection integrated five exercises. We indicated for the student that he she can redo the same current exercise multiple times as long as he wishes. When the student feels that he wants to leave the room or when he finishes the exercises collection we thank him and we give him a post-experiment survey to be filled. Finally, we paid the participant and debriefed him. In each time we have a new participant, we redo the eye tribe calibration (Figure 7.2).

### 7.5.1 Experiment 1 Conditions

In experiment 1, we placed on the table next to the screen our robot ROBOMO (Figure 7.3). There are four conditions:

{item Condition 1: The robot affords a persuasive message before gamma window.
{item Condition 2: The robot affords a persuasive message after gamma window.
{item Condition 3: The robot affords a persuasive message during gamma window.
{item Condition 4: No persuasive message is afforded.

The persuasive message follows the technique that's not all. Example: Einstein tried multiple times to apply for a position in the faculty. However, his request was rejected many times. Perseverance he is one of the ingredients for success. That's not all... Leonel Messi had a problem related to walking but he insisted on trying to work and then becomes an incredible Runner. Insisting on achieving one's goals is rentable. That's not all... As long as you try to understand the difficult exercises you are spending more time and according to Harvard table of calories lose, you can burn in 30 minutes up to 50 calories just by concentrating so there is no big deal to take your time.

### 7.5.2 Experiment 2 Conditions

Based on the first experiment we can determine which of the different periods is the most suitable period during which the persuasive message source could deliver the persuasive message. In our second experiment, we considered to verify which of the two students' profiles will be more influenced by the persuasive message. We also want to investigate whether

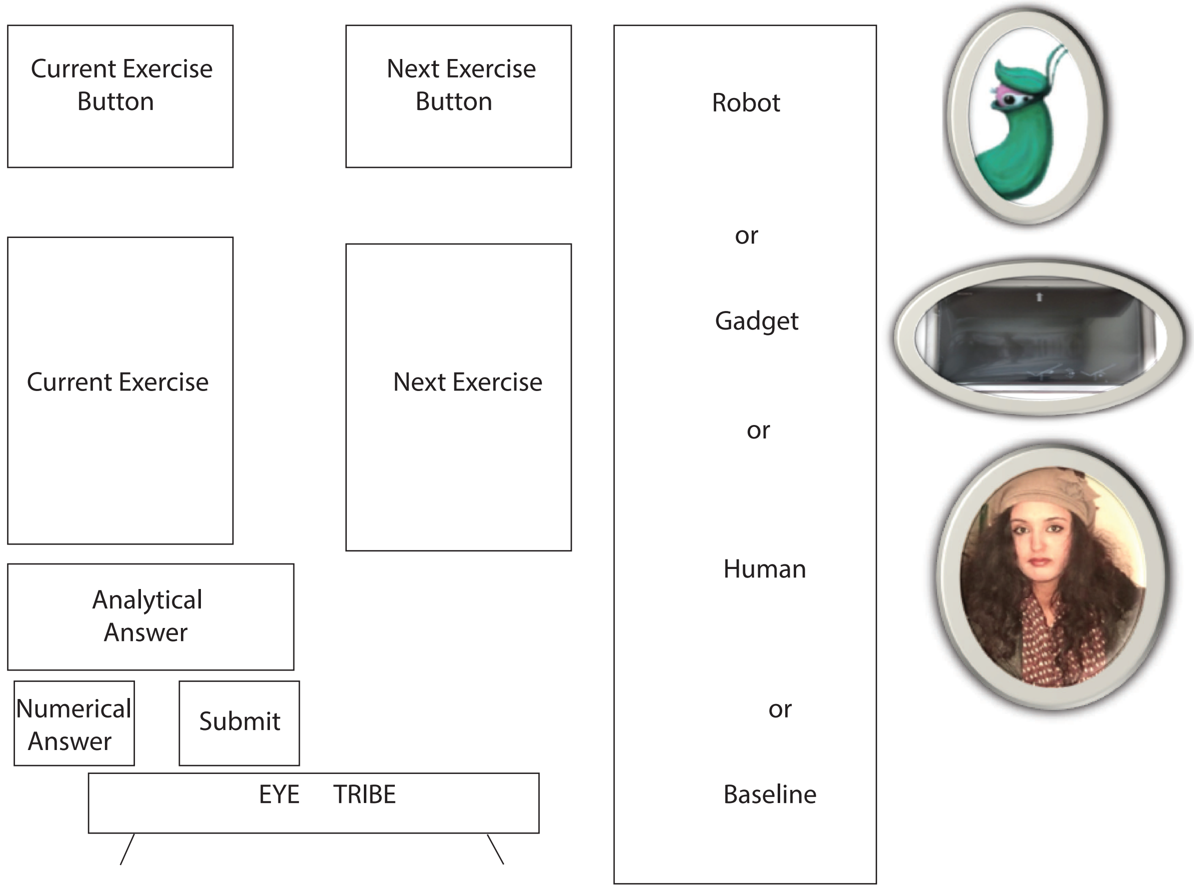



Fig. 7.3 The setup of the first experiment.

the persuasive message source agency has an influence on the persuasiveness degree. That is why, in the second experiment, we had four conditions (Figure 7.4):

{item Condition 1: Baseline condition (no persuasive message source). {item Condition 2: A box that includes the tablet showing the persuasive message textual format. {item Condition 3: The robot ROBOMO using speech, guestures, different tones, face tracking. The speech consist of the persuasive message text spoken by the robot. The gestures consist of the robot moving its head right and left to indicate a refusal, moving the head to indicate that the robot agrees with the student's behavior, moving the head backward high quickly to indicate that the robot was surprised, moving the head slowly to the front to indicate that the robot is sad, moving the body to the left, front and the right to indicate that the robot is happy. As for the tunes, they were generated by text-to Mary-speech. We conceived tones in a way that they could fit the robot guestures. The tone, the guestures and the robot's speech were synchronized. {item

Condition 4: The same tones, gestures and speech are used by a human as a persuasive message source.

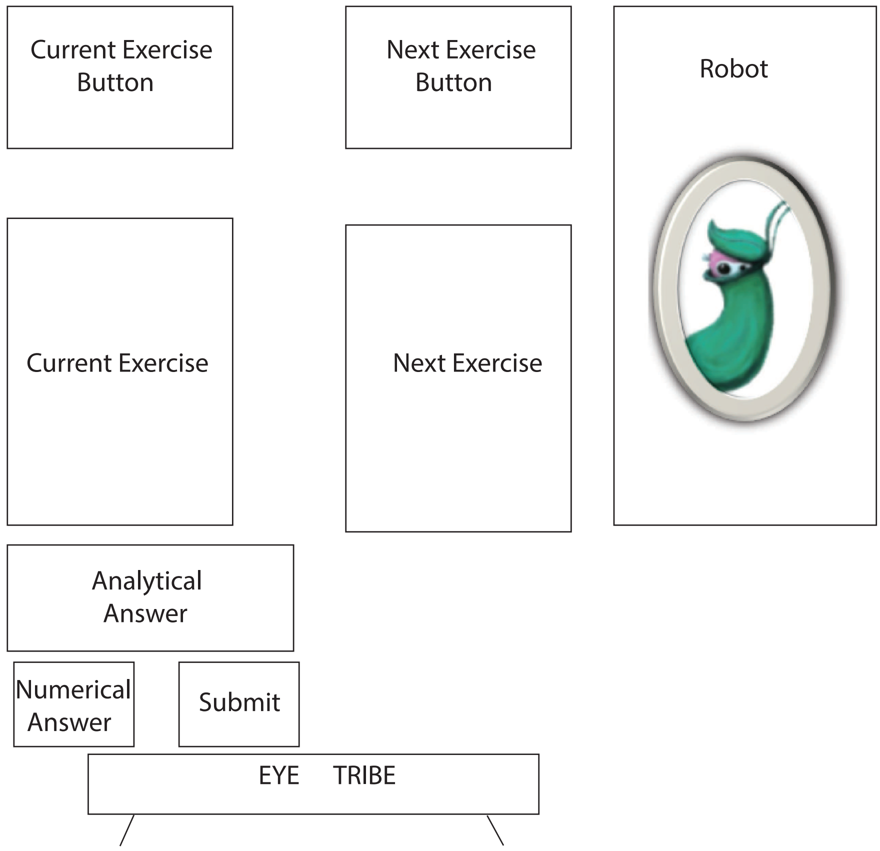



Fig. 7.4 The setup of the second experiment.

## 7.6 Survey

In each interaction's instance, the student has to fill a pre experiment survey and a post experiment survey. Questionnaires were written in English and French languages.

### 7.6.1 Pre-Experiment Survey

Initially, we asked the participant to write his age, gender. The student has to answer questionnaires related to self-esteem, NARS (to assess the student's anxiety when interacting with a robot), epistemological belief, need for cognition, prior knowledge, mood, cognitive closure, motivation to do the experiment, the student profile (utilitarian or relational).

### 7.6.2 Post-Experiment Survey

After the experiment finished, the student has to answer questionnaires related to the persuasive message source: Trust (to measure the student trust on the persuasive message source), likeability (to measure the student likeability for the persuasive message source), credibility (to measure the persuasive message source's credibility that it is perceived by the student), perceived intelligence(to measure the persuasive message source's level of intelligence that it is perceived by the student), the explicit attitude (by answering two questions:

- Why do you think you have rechecked or not the wrong answer?
- Do you think that you will consider redoing an exercise in the future when you makes an error while doing it?

), the implicit attitude (implicit association test) to verify whether the student evolved an implicit attitude that supports science learning (this is important to verify whether the student is convinced about the fact that he needs to strive for learning science rather than adopting a negative implicit attitude that supports learned helplessness).

## 7.7 Variables

### 7.7.1 First experiment variables

We have different independent and dependent variables related to our study.

#### Independent variables

In our second experiment, we have many independent variables such as: gender, age, self-esteem, NARS, epistemological belief, need for cognition, prior knowledge, cognitive closure, motivation to do the experiment.
We considered to measure the different independent variables to ensure we have the needed factors cited in the different science learning studies. We we wanted to have an equilibrated data set. For example: We wanted to high and low self esteem students. Also, we wanted to have the same number of females and males. NARS is measured to consider only students that have no social anxiety when interacting with a robot. We measured epistemological belief, need for cognition, prior knowledge, cognitive closure, motivation to do the experiment to be sure that the students have some knowledge about the science exercises that we consider to assign for the student, whether they believe that science is useful (we consider it to have a bit disciplined students who believe on the utility of science (do not suffer

from learned helplessness)), whether in their daily life they look for consonant concepts in general. We considered three ages (16 17 18 years old).

#### Dependent Variables

As for the dependent variables we have: cognitive dissonance, dominance, likeability, perceived intelligence (pintelligence), implicit attitude (IAT). We have also some other dependent variables which are measured using eye tribe and the mouse listener. We may enumerate them as follows:

- The quotient: Number of times the user redoes the exercise when it is incorrect/ number of times the user makes an error.
- FWhenMSGisdelievered: % of frames looking to the message source when the message is delivered
- FAfterMSGisdelievered: % of frames during which the user looks to the source after the message is delivered. (eye gaze)
- Nbtimeslooksbwexercises: number of times the user "dwells" with eye gaze between the 2 exercises before taking the decision to redo the current exercise that was previously answered in an incorrect way (eye gaze).
- Nbtimesmovesmousebwexercises: number of times the user "dwells" with mouse movement between the 2 exercises before taking the decision to redo the current exercise that was previously answered in an incorrect way (mouse movement).

### 7.7.2 Second experiment variables

We have different independent and dependent variables related to our study.

#### Independent variables

In our second experiment, we have many and independent variables such as: gender, age, self-esteem, NARS, epistemological belief, need for cognition, prior knowledge, cognitive closure, motivation to do the experiment, the user's profile (utilitarian or relational).
We considered to measure the different independent variables to ensure we have the needed factors cited in the different science learning studies. We we wanted to have an equilibrated data set. For example: We wanted to high and low self esteem students. Also, we wanted to have the same number of females and males. NARS is measured to consider only students

that have no social anxiety when interacting with a robot. We measured epistemological belief, need for cognition, prior knowledge, cognitive closure, motivation to do the experiment to be sure that the students have some knowledge about the science exercises that we consider to assign for the student, whether they believe that science is useful (we consider it to have a bit disciplined students who believe on the utility of science (do not suffer from learned helplessness)), whether in their daily life they look for consonant concepts in general. We considered three ages (16 17 18 years old).

#### Dependent Variables

As for the dependent variables we have: cognitive dissonance, mood (pleasure, dominance, arousal), trust, likeability, credibility, perceived intelligence (pintelligence), explicit attitude (free answers), implicit attitude (IAT). We have also some other dependent variables which are measured using eye tribe and the mouse listener. We may enumerate them as follows:

- The quotient: Number of times the user redoes the exercise when it is incorrect/ number of times the user makes an error.
- FWhenMSGisdelievered: % of frames looking to the message source when the message is delivered
- FAfterMSGisdelievered: % of frames during which the user looks to the source after the message is delivered. (eye gaze)
- Nbtimeslooksbwexercises: number of times the user "dwells" with eye gaze between the 2 exercises before taking the decision to redo the current exercise that was previously answered in an incorrect way (eye gaze).
- Nbtimesmovesmousebwexercises:number of times the user "dwells" with mouse movement between the 2 exercises before taking the decision to redo the current exercise that was previously answered in an incorrect way (mouse movement).

### 7.7.3 Categorization of the variables

We may categorize these variables into two categories: subjective and objective variables.

#### Categorization of the first experiment variables

In the case of the first experiment, the subjective variables include:

- cognitive dissonance.

- dominance.
- likeability.
- perceived intelligence (pintelligence).
- implicit attitude (IAT).

While the objective variables include:

- The quotient.
- FWhenMSGisdelievered.
- FAfterMSGisdelievered.
- Nbtimeslooksbwexercises.
- Nbtimesmovesmousebwexercises.

**Categorization of the second experiment variables**

In the case of the second experiment, the subjective variables include:

- cognitive dissonance.
- dominance.
- pleasure.
- arousal.
- trust.
- credibility.
- likeability.
- perceived intelligence (pintelligence).
- implicit attitude (IAT).
- explicit attitude.

While the objective variables include:

- The quotient.
- FWhenMSGisdelievered.
- FAfterMSGisdelievered.
- Nbtimeslooksbwexercises.
- Nbtimesmovesmousebwexercises.

## 7.8 Demographics

We conducted two experiments with different number of participants. The G*Power software was used to determine an appropriate sample size for the proposed experiments. G*Power is an open source statistical software primarily used for power analysis. An a Priori Power Analysis calculation given an error probability value ($/alpha$= 0.05), power (P=0.95), and effect size (f=0.25) revealed the need for a total sample size of 66 participants (N=66) as for experiment 2 and more than 35 participants for experiment 1.

### 7.8.1 Demographics of the first experiment

40 students took part in our experiment while 33 are utilitarian and 33 are relational. From the utilitarian students, we have 20 males and 20 females. They were hired via their teachers. The teachers have helped us as well to identify students that have low science learning capacities.

### 7.8.2 Demographics of the second experiment

66 students took part in our experiment while 33 are utilitarian and 33 are relational. From the utilitarian students, we have 20 males and 13 females. As for the relational students we have 15 males and 18 females. We noticed that utilitarian students are high self-esteem students while relational students are low self-esteem student. This may explain partly if we have better results in terms of persuasiveness in the case of relational students the reason why such relational students are easy to be persuaded in comparison to the others. In fact, high self esteem people are difficult to be influenced because they believe that they are more powerful, smart and they stick to the positive innate illusions to protect their public self-images. Students are hired from a tunisian college (in Tunisia). They were hired via their teachers to the experiment. The teachers helped us to better choose the students who start

to have problems with science learning. They even have identified the weak points for each of the different students (without that the students know about that).

## 7.9 Analysis Methods

The analysis of data on manipulation checks followed a repeated measures analysis of variance (ANOVA) for the first experiment while a mixed two-way repeated measures ANOVA was used to analyze the data of the second experiment. These tests included Omnibus tests to identify general effects of the experimental manipulation on dependent variables and contrast tests that compared the different conditions for the case of two way ANOVA of the second experiment.

## 7.10 First experiment results

So, as a reminder, the hypothesis H1 of the first experiment (H1E1): "consists on *comparing the persuasive message effect when the message is spoken "during gamma window", "after gamma window", "before gamma window" and a baseline condition when "no persuasive message is proposed by the persuasive source"*.

### 7.10.1 Subjective results

Table 7.1 The tests of within-subjects effects table for the different subjective measures to indicate whether there was an overall significant difference between the means at the different time points.

| | **(F,P-value, $eta^2$)** |
|---|---|
| Dominance | (23.93, p<0.001, 0.38) |
| IAT | (39.27,p<0.001, 0.502) |
| Perceived Intelligence | (99.5,p<0.001, 0.718) |
| Cognitive dissonance | (69.93, p<0.001, 0.642) |
| Likeability | (104.8,p<0.001, 0.729) |

Based on the results there were no violation of the sphericity assumption. Table shows the results of the ANOVA for the within subjects variable. There is a sum of squares for the within subject effect of each of the different subjective variables. The p-value of each of the different subjective constructs is inferior than 0.001 which means that there were significant differences between the different conditions:" before gamma", " after gamma"," during gamma" and the baseline condition.

Table 7.2 Repeated measures ANOVA helping to compare the "gamma condition" with the "no gamma condition" and the "gamma condition" with the "before gamma condition" in terms of subjective measures. In each of the two last columns, we have the F-test, p-value and the $eta^2$ that describes the effect size.

| | **G VS no G (F,p,$eta^2$)** | **G VS B (F,p,$eta^2$)** |
|---|---|---|
| Dominance | (75.6,P<0.001,0.66) | (34.54,p<0.001, 0.447) |
| IAT | (155.37,p<0.001, 0.79) | (3.29, 0.07) |
| Perceived Intelligence | (256.05, p<0.001, 0.868) | (133.32, p<0.001, 0.774) |
| Cognitive dissonance | (127.14, p<0.001, 0.765) | (44.89, p<0.001, 0.535) |
| Likeability | (479.9,p<0.001, 0.927) | (151.6, p<0.001, 0.795) |

By looking at tables 7.2 7.3 7.4, we can see that there were significant differences between the different conditions except for the case of the implicit association test (IAT) when we compare the conditions "during gamma window" vs "before Gamma window", the perceived intelligence when we compare ’after Gamma window" vs "no message"(baseline condition), for the case of dominance when we compare "after Gamma window" with the "before Gamma window" conditions and the cognitive dissonance when we compare the "after gamma window" and the "no Gamma window".

Table 7.3 Repeated measures ANOVA helping to compare the "after gamma condition" with the "before gamma condition" and the "no gamma condition" with the "before gamma condition" in terms of subjective measures. In each of the two last columns, we have the F-test,p-value and the $eta_2$ that describes the effect size.

| | **A vs B (F,p,$eta^2$)** | **No G vs B (F,p,$eta^2$)** |
|---|---|---|
| Dominance | (0.05,0.943) | (9.82,p=0.003, 0.2) |
| IAT | (9.13, 0.004, 0.19) | (70.55,p <0.001, 0.644) |
| Perceived Intelligence | (17.29, p <0.001, 0.307) | (47.9,p <0.001, 0.551) |
| Cognitive dissonance | (27.4, p <0.001, 0.535) | (45.985, p <0.001, 0.541) |
| Likeability | (13.2,0.001, 0.253) | (50.8, p <0.001, 0.566) |

Based on these results, we can deduce that proposing a message for the participant after the gamma window does not make the robot looks intelligent, has no effect on the cognitive dissonance and as a result has no effect on the implicit attitude formation, an attitude that should support the strive to understand the science exercise or more explicit words an attitude that dictates spontaneously for the human to redo the current exercise that was previously answered in an incorrect way.

In table 7.1, we colored in blue the constructs that have significant results. In table 7.2, we colored in pink the constructs that have significant results. The pink color indicates that the "gamma window" condition mean value for each of the subjective variable is higher than

Table 7.4 Repeated measures ANOVA helping to compare the "gamma condition" with the "after gamma condition" and the "after gamma condition" with the "no gamma condition" in terms of subjective measures. In each of the two last columns, we have the F-test,p-value and the $eta_2$ that describes the effect size.

| | **G vs Af (F,p,$eta^2$ )** | **A vs no G (F,p,$eta^2$ )** |
|---|---|---|
| Dominance | (19.56,p< 0.001, 0.334) | (14.84,p< 0.001, 0.27) |
| IAT | (20.79, p< 0.001, 0.348) | (16.7, p< 0.001, 0.336) |
| Perceived Intelligence | (153.9, p< 0.001, 0.798) | (0.091, 0.764) |
| Cognitive dissonance | (27.4, p< 0.001, 0.413) | (0.943, 0.34) |
| Likeability | (151.6, p< 0.001, 0.795) | (0.64, 0.427) |

the mean of the same variable in the condition "before gamma" and the baseline condition. Consequently, a message that it is proposed during "gamma window" leads to a stronger feeling that the robot is dominant, intelligent, likeable and that the situation is governed by higher cognitive dissonance when a persuasive message is pronounced during the gamma window. This could be explained by the fact that students become more aware that they should take the situation more seriously once they are choking under the stress of the incorrect answer.

In table 7.3, we colored in yellow the constructs that have significant results. The yellow color indicates that the "before gamma window" condition mean value for each of the subjective variable is higher than the mean of the same variable in the conditions "after gamma"and the baseline. Based on the table 7.3, it is clear that when a persuasive message source is received before the human makes an error makes, the robot starts to look more likeable, intelligent, triggers higher cognitive dissonance and leads to higher implicit association tests (a test showing that users evolve the implicit attitude to continue with the current exercise if the corresponding answer was incorrect.) in comparison to the baseline condition and the "after gamma window". We also remark that the robot will be more dominant in conditions "before gamma window" in comparison to the baseline condition. Consequently, one can conclude that having a message that it is delivered before the gamma window have a more positive influence on the user's global evaluation of the robot's traits (likeable, intelligent), stronger awareness about the cognitive dissonance critical situation and leads to the formation of a more positive spontaneous attitude activated by the automatic processing system in comparison to the situations when the message is delivered "after the gamma window" or when no message is delivered (baseline condition).

In table 7.4, we colored in pink and green the constructs that have significant results. The pink color indicates that the "before gamma window" condition mean value for each of the subjective variables is higher than the mean of the same variable in the condition "after

Table 7.5 Repeated measures ANOVA helping to compare the objective results of the different conditions ("after gamma condition", "before gamma condition", "no gamma condition", "gamma condition"). In each of the last column, we have the F-test,p-value and the $eta_2$ that describes the effect size.

| **Factor** | **(F,P-value, $eta^2$)** |
|---|---|
| FAfterMSGisdelievered | (27.29, $<$ 0.001, 0.412) |
| FwhenMSGdelivered | (44.27, p$<$ 0.001, 0.532) |
| Nbtimesmousemovesbwexercises | (121.37, p$<$ 0.001, 0.757) |
| Errorquotient | (14.97, p$<$ 0.001, 0.277) |
| Nbtimelooksbwexercises | (53.49, p$<$ 0.001, 0.578) |

gamma". The green color indicates that the "after gamma window" condition mean value for each of the subjective variables is higher than the mean of the same variable in the baseline condition. When we compare subjective results for the " gamma window" and the " after gamma window" conditions, we can see that there are significant results and that the pink color prevails in the different cells indicating that participants felt that the robots is more dominant, intelligent, likeable and leads to the involvement of a more positive implicit attitude. It also triggers more cognitive dissonance.

When we compare the results of the conditions " after gamma window" with the Baseline condition witty remark that there are significant statistical differences. The green Colour prevails as well indicating that the robot is more dominant and likeable when a message is delivered after the gamma window. However, there were no differences in terms of robot's intelligence and the cognitive dissonance that is triggered by the robot.

### 7.10.2 Objective results

The table 7.5 shows that there are many statistical differences for the different objective constructs. The blue color indicates that there are significant results with p-values inferior than 0.001. We applied the pairwise comparisons between the different condition in terms of objective results in the following tables.

Based on the table 7.6, it is clear that there were significant statistical differences in terms of objective measures. We use the pink color to indicate that the mean value of the objective construct in "gamma window" condition is higher than the mean value of the same objective construct in the Baseline condition and " before gamma window" condition. By looking at the table 7.6, one can see that the pink color prevails indicating that the participants have higher percentage of a frames during which they look to the robot after the message is delivered and when the message is delivered. Also, it indicates that the number

Table 7.6 Repeated measures ANOVA helping to compare the objective results of the "gamma condition" with the "no gamma condition" and the "gamma condition" with the "before gamma condition". In each of the two last columns, we have the F-test,p-value and the $eta_2$ that describes the effect size.

| **Factor** | **G VS no G (F,p, $eta^2$)** | **G VS B (F,p, $eta^2$)** |
|---|---|---|
| FAfterMSGisdelievered | (38.7, p <0.001, 0.499) | (14.25, 0.001, 0.268) |
| FwhenMSGdelivered | (74.45, p <0.001, 0.656) | (165.09, p <0.001, 0.809) |
| Nbtimesmousemovesbwexercises | (12.45, 0.001, 0.242) | (188.28,p <0.001, 0.828) |
| Errorquotient | (40.72, p <0.001, 0.511) | (15.21, p <0.001, 0.281) |
| Nbtimelooksbwexercises | (155.85, p <0.001,0.8) | (188.285, <0.001, 0.828) |

Table 7.7 Repeated measures ANOVA helping to compare the objective results of the "gamma condition" with the "after gamma condition" and the "after gamma condition" with the "no gamma condition". In each of the two last columns, we have the F-test,p-value and the $eta^2$ that describes the effect size.

| **Factor** | **G vs Af (F,p,$eta^2$)** | **A vs no G (F,p,$eta^2$)** |
|---|---|---|
| FAfterMSGisdelievered | (44.93, <0.001, 0.535) | (1.1, 0.29) |
| FwhenMSGdelivered | (160.01,p <0.001, 0.801) | (3.69, 0.062) |
| Nbtimesmousemovesbwexercises | (8.48, 0.006, 0.179) | (38.6,p <0.001, 0.498) |
| Errorquotient | (25.34, p <0.001, 0.394) | (3.71, 0.061) |
| Nbtimelooksbwexercises | (73.12, p <0.001, 0.652) | (41.13, p <0.001, 0.513) |

of times during which the most is moving between the two exercises as well as the number of times during which the human is looking between the two exercises and finally the error quotient which indicates whether the student is a striving to understand the wrong answer car higher during " gamma window" condition. Consequently, even if the participant looks more perplexed we have someone moving mouse and a more movement in the eyes, he seems to be more convinced that he has to pay attention to the current exercise in comparison to the conditions " before gamma window" and the Baseline condition.

The table 7.7 shows that there are significant statistical differences between objective results of both conditions " during gamma window" and " after gamma window". The pink color was used to indicate that the mean value of each of the objective constructs is higher in the condition "during gamma window". We can see that in the first column, the pink color prevails. This indicates that the robot led to more consideration of the situation by the participant. That is why we noticed that the percentage of frames during which the participant is looking to the message source after the message is delivered, the percentage of frames during which the human is looking to the robot after the message is delivered, the number of times the human moves the mouse between the two exercises, the number of times the

Table 7.8 Repeated measures ANOVA helping to compare the objective results of the "after gamma condition" with the "before gamma condition" and the "no gamma condition" with the "before gamma condition". In each of the two last columns, we have the F-test,p-value and the $eta_2$that describes the effect size.

| **Factor** | **A vs B (F,p,$eta^2$)** | **No G vs B (F,p,$eta^2$)** |
|---|---|---|
| FAfterMSGisdelievered | (18.97, <0.001, 0.327) | (14.25, 0.001, 0.268) |
| FwhenMSGdelivered | (52.46, p<0.001, 0.574) | (17.95, p<0.001, 0.315) |
| Nbtimesmousemovesbwexercises | (3.52, 0.058) | (290.9, p<0.001, 0.882) |
| Errorquotient | (0.597, 0.44) | (9.02, 0.005, 0.188) |
| Nbtimelooksbwexercises | (0.463, 0.57) | (25.23, p<0.001, 0.393) |

participant looks between the two exercises are higher during the " gamma window" condition. Consequently, the error quotient increases indicating that the human is considering the situation in a more reasonable way by redoing the current exercise that was previously answer it in a wrong way.
The green color was used to indicate that the mean value of each of the objective constructs is higher in the condition "after gamma window". By looking to the second column, we can see that there were significant differences between "after gamma window" and the Baseline conditions in terms of the number of times the participant moving the mouse or the eye gaze between the two exercises. The green color was used to indicate that the mean value of each of the objective constructs is higher in the condition "after gamma window". So, although the participant seems to be more perplexed when a message is delivered "after the gamma window", there were no fruitful consequences one can see that the error quotient has no significant differences in comparison to the Baseline condition. Using a message after the "gamma window" may help to increase some of the subjective results. However, it is not enough to increase the error quotient which indicates that the participant is putting more effort to redo the wrong current exercise. The table 7.8 shows the objective results comparison of different conditions which are the " after gamma window" and the " before gamema window" as well as " before gamma window" and the Baseline conditions. We used the yellow color to indicate that the mean value of the objective construct is higher in the condition " before gamma window" in comparison to the Baseline condition and the " after gamma window". The green color was used to indicate that the mean value of the objective construct was higher in the condition " after gamma window" in comparison to " before gamma window". By looking the second column of the table 7.8, we can see that the yellow color prevails which indicates that globally it is better to have a persuasive message that is delivered before gamma window rather than the condition where there was no message that is delivered. By looking to the first column, we can see that the participant seems to look to

the robot after the message is delivered more when the message is delivered during gamma window. However, the student looks more to the Robot after the message is delivered when the latter is delivered after the gamma window (it seems to be like the human was surprised by the message because he has already taken his decision and there is no reason why the robot should talk). As for the error quotient, there where no statistical differences which indicates that using a message before or after gamma window is not useful enough to make the participant reconsiderate the current exercise that was previously answered in a wrong way. However, based on the second column, it seems to be that proposing the message before gamma window is better than proposing nothing. Generating a message after gamma window does not lead to better results in comparison to the Baseline condition while proposing the message during gamma window seems to lead to better results in comparison to all the other conditions.

## 7.11 Results of the Second Experiment

We applied the two way mixed repeated ANOVA analysis to investigate the three hypothesis that are related to the second experiment.

### 7.11.1 Hypothesis 1 Investigation

So, as a reminder, the hypothesis H1 of the second experiment (H1E2) consists on verifying whether*:" the more a participant scores high on the dimension of relational (vs utilitarian), the more that participant will be persuaded since we assume that they are more cooperative than utilitarian participants.*."

Table 7.9 shows that there were no violation of the sphericity end that Levin tests are not significant too which means that there were no main correction of the F-test values. The blue color in the tables 7.10 7.11 7.12 7.9 indicates that the results are significant why is the P-value values in the range of 0.031 and inferior than 0.001.
By applying the pairwise comparisons, for the subjective (table 7.9) and the objective (table 7.11) constructs, one can see that there were main differences between utilitarian and relational students.

Tables 7.12 7.10 show that relational students seem to have higher mean values for the objective constructs and the subjective measures except for the pleasure construct. These results indicate that the more a participant scores high on the dimension of relational (vs utilitarian), the more that participant will be persuaded since we assume that they are more cooperative than utilitarian participants.

Table 7.9 Two-way mixed repeated measures ANOVA subjective results that are related to the first hypothesis (first main effect: relational Vs utilitarian). In the first and second columns, we have sphericity and homogeneity test results. In column three, we have the between subject effect F and P-value results by means of the different constructs presented vertically.

| factor | Ma(W,pval) | Lev | (F, p-val) |
|---|---|---|---|
| Arousal | (0.98,0.5) | >0.05 | (5.6, 0.021) |
| Dominance | (0.979, 0.513) | > 0.05 | (4.214,0.044) |
| Trust | (0.95, 0.228) | > 0.05 | (10.6,0.002) |
| Pleasure | (0.98, 0.674) | > 0.05 | (4.84,0.031) |
| Credibility | (0.98,0.235) | > 0.05 | (33.38,p<0.001) |
| IAT | (0.84, 0.06) | > 0.05 | (4.18,0.045) |
| Perceived Intelligence | (0.97, 0.48) | > 0.05 | (33.22, p<0.001) |
| Cognitive Dissonance | (0.84, 0.064) | > 0.05 | (84.43,p<0.001) |
| Likeability | (0.947, 0.43) | > 0.05 | (71.311, p<0.001) |

Table 7.10 The mean and standard deviation of relational and utilitarian students by means of the different constructs presented vertically and which are related to the

| factor | Relat (M,sd) | Utilit (M,sd) |
|---|---|---|
| Arousal | (3.85,0.15) | (3.34,0.15) |
| Dominance | (3.313,0.14) | (2.89,0.14) |
| Trust | (39.41,1.4) | (32.99,1.4) |
| Pleasure | (3.22,0.169) | (3.74,0.169) |
| Credibility | (16.86,0.425) | (13.39,0.42) |
| IAT | (0.615,0.026) | (0.539,0.026) |
| Perceived Intelligence | (19.82,0.537) | (15.45,0.537) |
| Cognitive Dissonance | (18.44,0.389) | (13.39,0.38) |
| Likeability | (22.10,0.51) | (15.93, 0.51) |

Table 7.11 Two-way mixed repeated measures ANOVA objective results that are related to the first hypothesis (first main effect: relational Vs utilitarian). In the first columm, we have Maulchy's test results. In column number two we have Leven test results. In column three, we have the between subject effect F and P-value results.

| factor | Ma(W,pval) | Lev | (F, p-val) |
|---|---|---|---|
| FAfterMSGisdelievered | (0.92, 0.09) | >0.05 | (103.7, p <0.001) |
| FwhenMSGdelivered | (0.95, 0.239) | > 0.05 | (52.4,p <0.001) |
| Nbtimesmousemovesbwexercises | (0.88, 017) | > 0.05 | (61.5,p <0.001) |
| Errorquotient | (0.90, 0.208) | > 0.05 | (10.93,0.002) |
| Nbtimelooksbwexercises | (0.93, 0.54) | > 0.05 | (98.02, p <0.001) |

Table 7.12 Two-way mixed repeated measures ANOVA objective results that are related to the first hypothesis (first main effect: relational Vs utilitarian). We have in the last two columns, the mean and standard deviation of relational and utilitarian students and by means of the different constructs presented vertically.

| factor | Relat (M,sd) | Utilit (M,sd) |
|---|---|---|
| FAfterMSGisdelievered | (9.53,0.29) | (5.23,0.29) |
| FwhenMSGdelivered | (5.76,0.19) | (3.74, 0.19) |
| Nbtimesmousemovesbwexercises | (6.492,0.18) | (4.485, 0.18) |
| Errorquotient | (0.516,0.02) | (0.413, 0.02) |
| Nbtimelooksbwexercises | (13.10,0.34) | (8.23, 0.34) |

### 7.11.2 Hypothesis 2 Investigation

As a reminder, hypothesis 2 of the experiment 2 (H2E2) *consists on investigating whether there is a main effect of the persuader's social agency type. That is, we expect that when a participant interacts with a gadget in a box, he or she will be persuaded less than when that participant interacts with a robot, in which situation the participant will be persuaded less than when that participant will interact with a human and of course having a persuasive source is better than nothing (the baseline condition).*

Table 7.13 Two-way mixed repeated measures ANOVA subjective results that are related to the second hypothesis (second main effect: baseline vs box vs human vs robot). We have in the second column, the F and p-value by means of the different constructs presented vertically and whenever the statistical differences are significant, we color the corresponding cell with the blue color.

| Factor | Main Comp |
|---|---|
| | (F,P-value) |
| Arousal | (16.06, $p < 0.001$) |
| Dominance | (64.76, $p < 0.001$) |
| Trust | (67.51, $p < 0.001$) |
| Pleasure | (84.51, $p < 0.001$) |
| Credibility | (79.55, $p < 0.001$) |
| IAT | (52.98, $p < 0.001$) |
| Perceived Intelligence | (232.16, $p < 0.001$) |
| Cognitive dissonance | (16.06, $p < 0.001$) |
| Likeability | (302.716,$p < 0.001$) |

Based on the table 7.13, we can see that there are significant within subject effect differences (the blue color prevails in the cells of the second column). Thus, we applied the pairwise comparisons.

Table 7.14 Two-way mixed repeated measures ANOVA subjective results that are related to the second hypothesis (second main effect: baseline vs robot; human vs robot; box vs robot) by means of the different constructs presented vertically.

| **Factor** | **Pairwise Comparisons (F, P-value)** | | |
|---|---|---|---|
| | Box VS robot | Robot vs human | Baseline vs robot |
| Arousal | (27.44,p < 0.001) | (2.25,p=0.138) | / |
| Dominance | (115.96, p <0.001) | (93.12,p <0.001) | / |
| Trust | (117.71,p <0.001) | (54.54, p <0.001) | / |
| Pleasure | (149.305, p <0.001) | (83.58, p <0.001) | / |
| Credibility | (147.92,p <0.001) | (67.82,p <0.001) | / |
| IAT | (21.92,p <0.001) | (2.293, p=0.135) | (103.005, p <0.001) |
| Perceived Intelligence | (431.7,p <0.001) | (171.94, p <0.001) | / |
| Cognitive dissonance | (136.8,p <0.001) | (88.57,p <0.001) | (180.12,p <0.001) |
| Likeability | (578.05,p <0.001) | (242.6, p <0.001) | / |

Based on the table 7.14, we can say that there were significant statistical differences in terms of subjective constructs whenever we use the robot as a persuasive message source that it is compared to the different other persuasive message sources. there were no differences in terms of IAT (implicit association test) which means that the human and the robot have the same effect on the cognitive miser.

Table 7.15 Two-way mixed repeated measures ANOVA subjective results that are related to the second hypothesis (second main effect: baseline vs box; baseline vs human; human vs box) by means of the different constructs presented vertically.

| **Factor** | **Pairwise Comparisons (F, P-value)** | | |
|---|---|---|---|
| | Box VS human | Baseline vs human | Baseline vs box |
| Arousal | (18.14, p < 0.001) | / | / |
| Dominance | (0.521,p=0.473) | / | / |
| Trust | (15.99, p <0.001) | / | / |
| Pleasure | (16.34, p <0.001) | / | / |
| Credibility | (12.79,0.001) | / | / |
| IAT | (37.54, p <0.001) | (165.56, p <0.001) | (17.91, p <0.001) |
| Perceived Intelligence | (65.38, p <0.001) | / | / |
| Cognitive dissonance | (17.97,p <0.001) | (40.4,p <0.001) | (2.15, p=0.14) |
| Likeability | (63.31, p <0.001) | / | / |

Based on the table 7.15, we notice that there were statistical differences between the baseline vs box conditions except for the cognitive dissonance while they (baseline and the box) seem to lead to the same level of cognitive dissonance; baseline vs human conditions and the human vs box conditions except for the dominance construct which means that the box and the human dominance are equal which we did not expect.

Table 7.16 The mean and standard deviations of the subjective results and which are related to the second hypothesis (baseline, box, human, robot) by means of the different subjective constructs with blue color indicates that the condition holds the highest results in terms of the subective measure, then comes the pin color after that the green color and lowest results are colored with the gray color for each of the different measures ([1]blue; [2]pink;[3]green; [4]gray.).

| | Baseline (m,sd) | Box (m,sd) | Robot (m,sd) | Human (m,sd) |
|---|---|---|---|---|
| Arousal | / | (2.75,0.16) | (4.22,0.21) | (3.81,0.18) |
| Dominance | / | (2.24,0.16) | (4.65,0.18) | (2.42,0.16) |
| Trust | / | (26.65,1.47) Ψ | (48.48,1.77) | (33.47,1.14) Ψ |
| Pleasure | / | (2.09,0.209) | (5.25,0.18) | (3.1,0.16) |
| Credibility | / | (12.03,0.44) | (19.37,0.47) | (13.98,0.46) |
| IAT | (0.217,0.037) | (0.483,0.047) | (0.77,0.039) Ψ | (0.838,0.03) Ψ |
| PIntelligence | / | (11.97,0.346) | (24.56,0.605) | (16.39,0.546) |
| Cog.dissonance | (11.621,0.5) Ψ | (12.712,0.588) Ψ | (23.561,0.728) | (15.788,0.369) |
| Likeability | / | (12.21,0.425) | (27.83,0.531) | (17.01,06) |

Based on the table 7.16, one can see that the blue color that it is related to the condition which leads to the highest results prevails in the robot's condition while in the human's condition, the blue color existed only for the IAT (implicit association test). However, using ($/Psi$) indicates that there are no significant results. So, globally, there were main differences between the robot and human conditions with the robot having higher subjective results. The robot leads to higher arousal, is more dominant, trustworthy, pleasant, credible, intelligent, likeable and triggers higher cognitive dissonance.

The box condition seems to lead to higher results than the baseline condition but lower to the human conditions while there were no significant differences between the human and box conditions in terms of trust. Also, there were no special difference in terms of cognitive dissonance between the box and baseline conditions.

As a summary, students seem to appreciate the presence of a robot that delivers the message during gamma window more than the human while there were no differences in terms of implicit attitude formation. The human presence is better than the box's presence while the baseline condition has the worst subjective results.

Table 7.17 shows that there are many main statistical differences between the different conditions. That it is why, we applied the pairwise comparisons. Table 7.18 shows that there were significant statistical differences whenever we consider to compare the robot condition with the other conditions.

Table 7.17 Two-way mixed repeated measures ANOVA objective results that are related to the second hypothesis (second main effect: baseline vs box vs human vs robot) for the different constructs presented vertically.

| Factor | Main Comp |
|---|---|
| | (F,P-value) |
| FAfterMSGisdelievered | (37.91, p<0.001) |
| FwhenMSGdelivered | (35.09, p<0.001) |
| Nbtimesmousemovesbwexercises | (165.47, p<0.001) |
| Errorquotient | (16.56, p<0.001) |
| Nbtimelooksbwexercises | (59.74, p<0.001) |

Table 7.18 Two-way mixed repeated measures ANOVA objective results that are related to the second hypothesis (second main effect: robot vs box; human vs robot; baseline vs robot) for the different constructs presented vertically.

| Factor | Pairwise Comparison (F-test, P-value) | | |
|---|---|---|---|
| | Box VS robot | Robot vs human | Baseline vs robot |
| FAfterMSGisdelievered | (55,66, p <0.001) | (42.91, p <0.001) | / |
| FwhenMSGdelivered | (18.34, p <0.001) | (14.65, p <0.001) | / |
| Nbtimesmousebwexs | (240.84, p <0.001) | (284.16, p <0.001) | (407.36, p <0.001) |
| Errorquotient | (26.09,p <0.001) | (18.63, p <0.001) | (48.73, p <0.001) |
| Nbtimelooksbwexs | (84.4, p <0.001) | (71.08, p <0.001) | (155.05, p <0.001) |

Table 7.19 Two-way mixed repeated measures ANOVA objective results that are related to the second hypothesis (second main effect: baseline vs box vs human vs robot). In the table, we have the different pairwise comparisons (Box VS human), (Baseline vs box) and (Baseline vs human) for the different constructs presented vertically.

| Factor | Pairwise Comparison (F-test, P-value) | | |
|---|---|---|---|
| | Box VS human | Baseline vs box | Baseline vs human |
| FAfterMSGisdelievered | (5.96, 0.017) | / | / |
| FwhenMSGdelivered | (79.04, <0.001) | / | / |
| Nbtimesmousemovesbwexercises | (8.49,0.005) | (9.75,0.003) | (38.6,<0.001) |
| Errorquotient | (0.517,0.475) | (2.212,0.142) | (7.9,<0.001) |
| Nbtimelooksbwexercises | (0.054,0.817) | (21.47,<0.001) | (14.112,<0.001) |

Based on table 7.19, we notice that there were significant statistical differences between the box and the human conditions except for two construct which are the error quotiet and the number of times the human looks between the two exercises. There were also significant differences between the baseline and box conditions except for the same construct (error quotient). By comparing the box and the baseline conditions, it is clear that there were no differences between both conditions when we consider the error quotient construct. Finally it is clear that there are always statistical differences between the baseline and human conditions in terms of objective measures. To determine the evolution's tendency of each of the

Table 7.20 The mean and standard deviation values for the baseline and box conditions and for the different constructs presented vertically.

| | Baseline (m,sd) | Box (m,sd) |
|---|---|---|
| FAfterMSGisdelievered | / | (5.56,0.34) |
| FwhenMSGdelivered | / | (3.27,0.27) |
| Nbtimesmousemovesbwexercises | (3.58,0.171) | (4.35,0.21) |
| Errorquotient | (0.353,0.028) | (0.42,0.032) |
| Nbtimelooksbwexercises | (10.01,0.422) | (7.72,0.34) |

objective constructs, tables 7.20 and 7.21 show in pink the condition that have the highest values for each of the different objective constructs (for example Errorquotient is colored in pink [1] when it is associated to the robot's condition. This means that the robot's condition leads to the highest results in terms of errorquotient in comparison to the other conditions.), then comes the blue color [2] that it is related to the second highest values for each of the different objective constructs, after that we have the green color [3] and finally the gray color [4] (Example: for the error quotient, we can see that the highest results are in the case of the robot condition (pink[1]), the second highest results are in the human condition (blue[2]), then comes the box condition with the third highest results(green [3])). Finally, we have the lowest results in term of error quotient in the baseline condition (gray[4]).)
Based on tables 7.20 and 7.21, we can see that globally the highest objective results were in the robot's condition except the number of frames during which the user is looking to the persuasive message source (FwhenMSGdelivered) while the human condition holds the highest results. After that comes the human condition that holds the second highest results except for two constructs which are the FwhenMSGdelivered and the number of times the student looks between exercises before choosing to redo the current exercise (Nbtimelooks-bwexercises) because it is the baseline condition that holds the second highest results. The third highest results belong to the box's condition except for the Nbtimelooksbwexercises (the baseline condition holds the third highest results) and finally comes the baseline condition that holds the lowest results.

In summary, strickigly, using the robot as a persuasive message source has the same effect on the evolved implicit attitude that encourages redoing the exercise that it is wrong. As for the other subjective results, it looks like the robot holds the highest results in comparison to the other conditions then comes the human condition, after that the box condition and finally comes the baseline condition with the lowest results.
In terms of objective results, it is the robot that holds the highest results as well except for

Table 7.21 The mean and standard deviation values for the robot and human conditions and for the different constructs presented vertically.

| | **Robot (m,sd)** | **Human (m,sd)** |
|---|---|---|
| FAfterMSGisdelievered | (9.88,0.45) | (6.71,0.28) |
| FwhenMSGdelivered | (4.88,0.25) | (6.12,0.197) |
| Nbtimesmousemovesbwexercises | (8.89,0.23) | (5.14,0.204) |
| Errorquotient | (0.633,0.031) | (0.452,0.029) |
| Nbtimelooksbwexercises | (15.06,0.47) | (9.87,0.47) |

the FwhenMSGdelivered and this could be explained by the fact that the human's presence could give to the student's the sensation that the human is staring at him/her so that it is why by social compliance, students look to the human too. After, the robot condition comes the human's condition with the second highest results globally, followed by the box condition and the worst objective results were in the baseline condition.

### 7.11.3 Hypothesis 3 investigation

**subjective results**

As a reminder, our third hypothesis of *the second experiment (H3E2) can be formulated as follows: We expect, most importantly, an interaction between the manipulation of persuader social agency and persuaded relational-utilitarian type. We are interested in whether the persuader's agency is equally effective for utilitarian and relational people (it is the change in the simple main effect of persuader's agency over levels of profile: 2 levels (utilitarian and relational)). That is, for people who are relational, they are more prone to follow equally the human or the robot's persuasive message rather than the box's persuasive message and overcome the cognitive dissonance.*
*In contrast, for people who are utilitarian, the effect of the persuasive message is of the same magnitude independently from the message's source but the presence of a persuasive message is better than the condition when there is no persuasive message (when the utilitarian human is left alone to face the cognitive dissonance).*

Based on the table 7.22 comparing the interaction effect (student's profile X the persuasive source's agency) in terms of subjective measures, we can see that there were significant results for whole the constructs while p-value varies from 0.04 to $< 0.001$ and that it is why all the cells of the second column were colored in blue (in fact in blue we colored the construct that have significant statistical differences when we compare the different interaction effects).

Table 7.22 The within subjects effect table of the interaction effect (comparing the baseline, robot, box and human conditions) related to the subjective measures and which correspond to the third hypothesis by means of the different constructs presented vertically

| **Factor** | **Main Comp** |
|---|---|
| | (F,P-value) |
| Arousal | (64.361,p=0.001) |
| Dominance | (9.008,p <0.001) |
| Trust | (13.73,p=0.04) |
| Pleasure | (3.64,p=0.029) |
| Credibility | (3.12,p=0.048) |
| IAT | (52.98,p <0.001) |
| Perceived Intelligence | (9.59,p <0.001) |
| Cognitive dissonance | (12.8,p=0.003) |
| Likeability | (11.98,p <0.001) |

Table 7.23 The pairwise comparison of the interaction effect values (box vs robot; robot vs human; baseline vs robot) related to the subjective measures by means of the different constructs presented vertically.

| **Factor** | **Pairwise Comparison (F-test, P-value)** | | |
|---|---|---|---|
| | Box VS robot | Robot vs human | Baseline vs robot |
| Arousal | (5.4, 0.023) | (112.94, p <0.001) | / |
| Dominance | (5.62,0.021) | (4.14,0.046) | / |
| Trust | (20.20,p <0.001) | (0.112,p=0.738) | / |
| Pleasure | (5.75,0.019) | (0.149,p=0.701) | / |
| Credibility | (5.44,0.023) | (0.137,0.712) | / |
| IAT | (0.1,0.753) | (069,0.409) | (5.12,p=0.027) |
| Perceived Intelligence | (18.28,p <0.001) | (5.34,p=0.024) | / |
| Cognitive dissonance | (16.68,p <0.001) | (16.93,p <0.001) | (180.12,p <0.001) |
| Likeability | (17.81,p <0.001) | (0.002,0.965) | / |

Based on the table 7.23, we can see that there were significant statistical differences in terms of arousal, dominance, perceived intelligence and cognitive dissonance (second column cells that are colored in blue). By comparing the robot and box conditions, we notice that there were significant differences for all the subjective values except for two constructs which are the IAT (implicit association test). Finally, by comparing the baseline and robot conditions, we can see that there are significant differences for the IAT and the cognitive dissonance.

In the same context, table 7.24 helps comparing the interaction effects between utilitarian and relational students while taking into account the persuasive message source agency level.

Table 7.24 The pairwise comparison of the interaction effect values (box vs human; baseline vs box; baseline vs human) related to the subjective measures by means of the different constructs presented vertically.

| **Factor** | **Pairwise Comparison (F-test, P-value)** | | |
|---|---|---|---|
| | Box VS human | Baseline vs box | Baseline vs human |
| Arousal | (81.11, p <0.001) | / | / |
| Dominance | (15.77,0.003) | / | / |
| Trust | (24.06,p <0.001) | / | / |
| Pleasure | (4.46,0.039) | / | / |
| Credibility | (4.56,0.037) | / | / |
| IAT | (0.099,0.754) | (5.17,p=0.026) | (11.11,p=0.001) |
| Perceived Intelligence | (4.429,p=0.039) | / | / |
| Cognitive dissonance | (0.945,0.335) | (2.158,p=0.147) | (40.40,p <0.001) |
| Likeability | (21.1,p <0.001) | / | / |

It is clear based on the first column of the table 7.24 that there were significant differences except for two measures which are the IAT and cognitive dissonance. By comparing the conditions baseline and human, we remark that there are significant differences in terms of IAT and cognitive dissonance and it is the same insight that we got when we compare the conditions baseline and box except the cognitive dissonance construct. We calculated the contrast

Table 7.25 Contrast Values related to hypothesis 3 of the different conditions (Robot-Box) and (Human-Box) for both types of profile (relational and utilitarian).

| | Robot-Box | | Human-Box | |
|---|---|---|---|---|
| | Rel | Util | Rel | Util |
| Arousal | (+) 0.82 | (+) 2.12 | (+) 3.3 | (+) -1.18 |
| Dominance | (+) 2.94 | (+) 1.88 | (+) 1.18 | (-) -0.82 |
| Trust | (+) 30.88 | (+) 12.79 | (+) 15.18 | (-) -1.55 |
| Pleasure | (+) 2.55 | (+) 3.79 | (+) 0.48 | (+) 1.55 |
| Credibility | (+) 8.76 | (+) 5.94 | (+) 3.12 | (+) 0.79 |
| IAT | (+) 0.27 | (+) 0.31 | (+) 0.37 | (+) 0.34 |
| Perceived Intelligence | (+) 15.18 | (+) 10 | (+) 5.58 | (+) 3.27 |
| Cognitive Dissonance | (+) 14.64 | (+) 7.06 | (+) 6.06 | (+) 0.09 |
| Likeability | (+) 18.36 | (+) 12.88 | (+) 7.58 | (+) 2.03 |

values that are related to the interaction effect (the student's profile X persuader's agency). Tables 7.25, 7.27 7.26 show the contrast values related to hypothesis 3 of the different conditions (Baseline-Box), (Human-Robot), (Robot-Box), (Human-Box), (Robot- Baseline) and (Human-Baseline) for both types of profile (relational and utilitarian). The blue color is related to the relational students group that hold the highest results for the construct that it is indicated in the first column, the pink color is associated to the utilitarian students group who have higher construct (indicated in the first column) results while in yellow we have the comparison that lead to no significant difference between both groups contrast values. Mainly, based on the tables 7.25, 7.27 7.26, we deduce that relational students have higher contrast values then the utilitarian students when we consider the robot-baseline, human-baseline conditions. Also, we remark that relational students have higher contrast values then the utilitarian students when we consider the robot-box, human-box conditions except for IAT and conitive dissonance where there were no significant differences and (arousal and pleasure) where utilitarian students have higher contrast values.

Table 7.26 Contrast Values related to hypothesis 3 of the different conditions (Robot-Baseline) and (Human-Baseline) for both types of profile (relational and utilitarian).

| | Robot-Baseline | | Human-Baseline | |
|---|---|---|---|---|
| | Rel | Util | Rel | Util |
| Arousal | / | / | / | / |
| Dominance | / | / | / | / |
| Trust | / | / | / | / |
| Pleasure | / | / | / | / |
| Credibility | / | / | / | / |
| IAT | (+) 0.68 | (+) 0.43 | (+) 0.78 | (+) 0.46 |
| Perceived Intelligence | / | / | / | / |
| Cognitive Dissonance | (+) 15.73 | (+) 8.15 | (+) 7.15 | (+) 1.18 |
| Likeability | / | / | / | / |

Based on the table 7.26, we remark that relational students are more sensitive to the shifting of the persuasive message source from baseline to robot and from baseline to the human as a persuasive source. Utilitarian students are also influenced by this shifting but with less proportions.

Now, if we compare the human-robot contrast values of the two groups (utilitarian and relational students), we remark that there were no main differences between both groups concerning the measures trust, pleasure, credibility and IAT which means that both groups find that the human and the robot are equally trustworthy, pleasant, credible and helps to evolve a positive implicit attitude that consists on redoing the science exercise when it is answered previously in an incorrect way. Always in the first comparison column of the table 7.27, there were negative evolution tendency of contrast values when we consider utilitarian students and this is reproduced for the constructs (arousal, dominance, perceived intelligence and cognitive dissonance). This means that as we have noticed previously that broadly speaking using a robot is better than using a human as a persuasive message source

Table 7.27 Contrast Values related to hypothesis 3 of the different conditions (Baseline-Box) and (Human-Robot) for both types of profile (relational and utilitarian).

| | Human-Robot | | Box-Baseline | |
|---|---|---|---|---|
| | Rel | Util | Rel | Util |
| Arousal | (+) 2.48 | (-) -3.3 | / | / |
| Dominance | (-) -1.76 | (-) -2.7 | / | / |
| Trust | (-) -15.7 | (-)-14.33 | / | / |
| Pleasure | (-) -2.06 | (-) -2.24 | / | / |
| Credibility | (-) -5.64 | (-) -5.15 | / | / |
| IAT | (+) 0.11 | (+) 0.03 | (+) 0.41 | (+) 0.12 |
| Perceived Intelligence | (-) -9.61 | (-) -6.73 | / | / |
| Cognitive Dissonance | (-) -8.58 | (-) -6.97 | (+) 1.09 | (+) 1.09 |
| Likeability | (-) -10.79 | (-)-10.85 | / | / |

and that relational students have higher subjective and objective results globally, by comparing the interaction effects, we can conclude that relational and utilitarian students are equally influenced by the usage of a robot or a human in terms of subjective measures (trust, pleasure, credibility, IAT) and sometimes the usage of a human could lead to more drastic subjective contrast results for utilitarian while the contrast values are negative which means that using a robot leads to positive contrast values. For some of the subjective results, we remark that perceived intelligence, cognitive dissonance and likeability have negative contrast values as for relational students which are higher if we consider the absolute value of the contrast results. Some of the subjective results show that using a human have higher interaction effect with a negative tendency for the utilitarian group, using a robot have higher interaction effect with a negative tendency for the relational group for some other subjective constructs and some have no special differences between both groups when we consider the comparison of the robot condition vs the human condition.

**objective results**

Table 7.28 the main comparison of the objective results related to hypothesis 3 (F,p-value).

| **Factor** | **Main Comp** |
|---|---|
| | (F,P-value) |
| FAfterMSGisdelievered | (9,p <0.001) |
| FwhenMSGdelivered | (3.623,p=0.029) |
| Nbtimesmousemovesbwexercises | (13.32, p <0.0001) |
| Errorquotient | (9.55,p <0.001) |
| Nbtimelooksbwexercises | (8.19,p=0.006) |

Table 7.29 The contrast objective values comparison of relational and utilitarian students for the comparisons (Human-Robot) and (Box-Baseline).

| | Human-Robot | | Box-Baseline | |
|---|---|---|---|---|
| | Rel | Util | Rel | Util |
| FAfterMSGisdelievered | -3.12 | -3.21 | / | / |
| FwhenMSGdelivered | (+) 1.12 | (+) 1.36 | / | / |
| Nbtimesmousemovesbwexercises | -4.36 | -3.15 | (+) 1.36 | (+) 0.18 |
| Errorquotient | -0.2 | -0.16 | (+) 0.22 | -0.08 |
| Nbtimelooksbwexercises | -5.36 | -5 | (+) 3.3 | (+) 1.27 |

Table 7.28 shows the statistical differences between the different conditions (persuader's agency) X (student's profile) while in blue we have the F-test values that led to statistical significant differences. By looking at the table 7.28, we remark that all the objective results F-tests have significant p-values and that it is why they were colored in blue.
By applying the comparison of both groups in conditions box-robot, box-human and robot-human, we remark that there were no significant results in terms of error quotient between the different interaction effect results. There were also no significant differences between contrast values of both groups when we consider the robot vs human condition in terms of FAfterMSGisdelievered and FwhenMSGdelivered. So both groups are equally influenced in terms of eye gaze movement when a cognitive dissonance occurs.

Table 7.30 Pairwise Comparison of the objective results related to hypothesis 3: 3 comparisons (Baseline vs box), (Baseline vs robot) and (Baseline vs human).

| **Factor** | **Contrast Values Pairwise (F, P-value)** | | |
|---|---|---|---|
| | Baseline vs box | Baseline vs robot | Baseline vs human |
| FAfterMSGisdelievered | / | / | / |
| FwhenMSGdelivered | / | / | / |
| Nbtimesmousemovesbwexercises | (5.7,p=0.02) | (36.45, p<0.001) | (15.16,p<0.001) |
| Errorquotient | (11.14,p=0.001) | (24.66,p<0.001) | (24.47,p<0.001) |
| Nbtimelooksbwexercises | (4.23,p=0.044) | (17.37,p<0.001) | (15.74,p<0.001) |

By considering the tables 7.30 and 7.29 , we can see that relational students are more influenced in a negative way when we change the persuasive message source from the robot to the human and that it is why it has higher results colored in blue as for the constructs Nbtimesmousemovesbwexercises and Nbtimelooksbwexercises.
Based on these objective contrast results, we can conclude that utilitarian students are equally influenced in comparison to the relational students and with the same evolution tendency in terms of eye gaze and error quotient and are less influenced than the relational

Table 7.31 The contrast objective values comparison of relational and utilitarian students for the comparisons (Robot-Baseline) and (Human-Baseline).

| | Robot-Baseline | | Human-Baseline | |
|---|---|---|---|---|
| | Rel | Util | Rel | Util |
| FAfterMSGisdelievered | / | / | / | / |
| FwhenMSGdelivered | / | / | / | / |
| Nbtimesmousemovesbwexercises | (+) 6.91 | (+) 3.73 | (+) 2.55 | (+) 0.58 |
| Errorquotient | (+) 0.48 | (+) 0.08 | (+) 0.28 | (-) -0.08 |
| Nbtimelooksbwexercises | (+) 9.79 | (+) 4.88 | (+) 4.42 | (-) -0.12 |

students in terms of Nbtimesmousemovesbwexercises and Nbtimelooksbwexercises. Based on the table 7.29, one can see that by comparing box-baseline condition objective results, relational students seen to be more sensitive to the shifting of the persuasive message source from the box to the baseline. Utilitarian are less sensitive to this shifting.

By considering tables 7.31 and 7.30 , we can see that relational students seem to be more influenced than utilitarian students if we shift the persuasive message source from the baseline to the robot. The evolution tendency of this influence is positive indicating that relational students prefer to have a robot as a persuasive message source rather than having no persuasive source. They also prefer the human as a persuasive message source rather than nothing and they are even more influenced than the utilitarian students again when we shift the persuasive message source from the baseline to the human. However, this time we can see that some of the utilitarian students do not prefer to have the human as a persuasive message source and that it is why the main contrast variable that indicates the number of times the human redoes the wrong exercise which is the error quotient decreases (-0.08) instead of increasing like as for the relational students (0.28). Even the Nbtimelooksbwexercises contrast value decreases too (-0.12) rather than that it increases whe we compare it to the relational students that were positively influenced when we shift the persuasive message source from the baseline to the human. Consequently, it seems to be that utilitarian students do not like the human's presence and it has a negative influence on the objective results.

Based on the tables 7.32 7.33, we can see that there were no statistical differences between the human and the box conditions in terms of Nbtimesmousemovesbwexercises, Errorquotient and Nbtimelooksbwexercises contrast values if we compare the evolution of these contrasts for the utilitarian and relational groups. However, there were significant differences between both group contrast values of the constructs FAfterMSGisdelievered and FwhenMSGdelivered where relational students seem to be more sensitive to the shifting of the persuasive message source from the box to the human. The same insight can be drew if we maintain the same constructs but the persuasive message source changes from the box to

Table 7.32 Pairwise Comparison of the objective results related to hypothesis 3: 3 comparisons (Box VS robot), (Box VS human) and (Robot vs human).

| **Factor** | **Contrast Values Pairwise (F, P-value)** | | |
|---|---|---|---|
| | Box VS robot | Box VS human | Robot vs human |
| FAfterMSGisdelievered | (10.36,p=0.002) | (16.37,p<0.001) | (0.009,p=0.925) |
| FwhenMSGdelivered | (5.11,p=0.027) | (5.153,p=0.027) | (0.139,p=0.71) |
| Nbtimesmousemovesbwexercises | (2.12,p=0.15) | (2.12,p=0.15) | (7.4,p=0.008) |
| Errorquotient | (5,p=0.03,) | (4.76,p=0.049) | (0.176,p=0.676) |
| Nbtimelooksbwexercises | (4.6,0.036) | (0.088,0.786) | (6.87,0.011) |

Table 7.33 The contrast objective values comparison of relational and utilitarian students for the comparisons (Robot-Box) and (Human-Box).

| | Robot-Box | | Human-Box | |
|---|---|---|---|---|
| | Rel | Util | Rel | Util |
| FAfterMSGisdelievered | (+) 6.18 | (+) 2.45 | (+) 3.06 | -0.76 |
| FwhenMSGdelivered | (+) 2.45 | (+) 0.76 | (+) 3.58 | (+) 2.12 |
| Nbtimesmousemovesbwexercises | (+) 5.55 | (+) 3.55 | (+) 1.18 | (+) 0.39 |
| Errorquotient | (+) 0.26 | (+) 0.16 | (+) 0.16 | 0 |
| Nbtimelooksbwexercises | (+) 6.48 | (+) 3.61 | (+) 1.12 | -1.39 |

the robot except that this time relational students again seem to have higher contrast values if we take into account the variable Nbtimelooksbwexercises.

## 7.12 Discussion

### 7.12.1 First Experiment Insights

Based on the first experiment, we remarked that there were significant statistical differences in terms of subjective and objective measures (tables 7.1 7.5 7.6 7.7). By looking to the different subjective constructs, we remark that "during gamma window" leads to higher subjective results if we compare it to the baseline (table 7.2), before gamma window (table 7.2) and after gamma window (table 7.4 ) except for one measure that it is IAT (implicit association test) when we compared "Gamma window" condition to "before gamma" condition. This indicates that both conditions lead to the same implicit attitude formation. An implicit attitude that incites according to the test to redoing difficult science exercices that were answered in a wrong way to strive for more success. Consequently, it is better to annouce a message during gamma window.
If we compare before gamma window condition to the other conditions (table 7.3), we re-

mark that "before gamma window" condition leads to the second highest results in terms of subjective results except for dominance where there were no statistical difference between after and before conditions indicating that proposing the message before or after has no effect on the dominance because it is maintained at the same level.
Now in terms of objective results (table 7.8), "before gamma window" condition seem to lead to higher results than the baseline condition. However, there were no special differences between "after gamma window" and "before gamma window" in terms of Nbtimesmousemovesbwexercises, Errorquotient, Nbtimelooksbwexercises which means that the message is proposed before or after the gamma window does not influence the mouse movement that dwells between the two exercises neither the eye gaze dwelling between the 2 exercises before making the final choice. It is the same level of dilemma then that we trigger when the message is triggered if the message is proposed before or after gamma window. Also, it is the same level of error quotient which means that proposing before or after gamma window may have some influence on the subjective evaluation of the persuasive message source but it has after all no special effect on the final decision taken by the student that it is related to the variable error quotient.
As for the FAfterMSGisdelievered , we remark that by comparing the after and before gamma (table 7.8) window conditions, we have higher results in the condition "after gamma window" because students were suprised when the robot suddently start talking after gamma window while it should have talked before that he/she takes the decision. they even indicated so when debriefed; One of the participant highlighted: "I think I was a bit surprised and sometimes annoyed when the robot start to talk while I am concentrating on redoing the current exercise." As for the FwhenMSGdelivered, it is the "before gamma window" that holds higher results than the "after gamma window" condition indicating that students are paying attention to the robot when the it talks eventhough they are concentrating on resolving the current exercise before that they are stricken by the cognitive dissonance. Students may accept so and do not accept it when they are redoing the current exercise because in the firt time (when the message is spoken before gamma window), the students are stricken by the exercise difficulty and the message distracted them from the difficulty, while when the message is spoken "after gamma window" and that the user has chosen to redo the current exercise [5], he needs his full concentration and that it is why the likeability is higher in the condition "before gamma window" rather than "after gamma window" (table 7.3).

[5] we count only the number of times when the student redoes the current exercise that was answered incorrectly and we do not considerate the number of times when the student rejects redoing the current exercise

### 7.12.2 Second Experiment Insights

**Hypothesis 1: Main Effect (Relational Vs Utilitarian)**

When comparing objective and subjective results (tables 7.11 7.9) of the relational and utilitarian students, we can conclude that there are significant differences between relational and utilitarian students. Based on the tables 7.107.12, we can see that relational students have the highest results if we do not take into consideration the persuasive message source. This gives us a first insight that relational students are easy to be influenced than utilitarian students. There were an exception for the pleasure construct, while we can notice based on the table 7.10 that utilitarian students have higher results than relational students.
Although, utilitarian students are known to be serious students and highly disciplined, they seem to be more enjoying the experiment. Using the debrief results, one of the utilitarian students says :"I enjoy myself while doing this experiment because finally I can see something new added to this old-fashioned education institution", another utilitarian students indicates:"It is wise to think about taking care of the courses that we take in a different way and I prefer to have something that can accompany me but I am sorry because I do not like that a human that accompany me to stare at me Let it be anything else that acts in a logical and reasonable way." Relational students were happy to conduct the experiment. But according to the statistical results, they were not happier than utilitarian students although relational students were supposed to feel positive emotions easily in comparison to the utilitarian students.

**Hypothesis 2: Main Effect (baseline vs gadget(box) vs robot vs human)**

Based on the tables 7.13 7.17, we can see that there were signficant statistical differences between the different conditions.
Pairwise comparisons in tables 7.14 7.15 7.18 7.19 show that there are manily signficant differences between all the conditions and for the different objective and subjective constructs except for:

- errorquotient when we compare box vs human and baseline vs box: This means that the usage of a box or a human is has the impact in terms of how many times the student decides to redo the current exercise that was answered previously in a wrong way.
- Nbtimelooksbwexercises when we compare box vs human: it seems to be that using a box or a human triggers the same eye gaze activity and thus the same dilemma level.

- Dominance when we compare the box and the human conditions: This means that both sources have the same level of dominance; Implicitly, we could deduce that the human's presence was not more captivating than a mere box that contains a gadget showing a text.
- cognitive dissonance: when we compare the baseline and the box. This means that using a box or nothing at all has no special imact on the cognitive dissonance that the student feels at least based on the student's subjective ratings because we should highlight that humans have in general a tendency to deny the occurence of any kind of cognitive dissonance and this is attributed to our natural tendency to maintain a good public image.
- IAT and arousal: when we compare the robot and the human conditions and this means that in both conditions (robot or the human), the student ended up with the same level of arousal and the same implicit conviction about the usefullness of redoing an incorrect exercise to understand one's errors.

Based on the tables 7.16 7.20 7.21, we can see that globally, the robot condition has the highest results, then comes the human condition, after that the box condition and finally we have the baseline condition with some exceptions related to some constructs.
if we focus on the conditions that have the highest impact in our reserach and which we can focus more, we can compare the robot and the human conditions The robot case has superior results than the human case except for the IAT while they seem to lead to the same implicit attitude formation's level ( an attitude that it is activated by the automatic processig system and which encourages learning more deeply science and redoing the wrongly answered exercises to learn tthe science concepts in a proper way). In terms of objective measures, we can mention that the "error quotient" is the dependent variable that mostly indicates whether the student was able to redo the exercise or not when it is answered the first time in a wrong way. By comparing error quotient results if conditions robot and human, we can say that the robot holds the highest results than the human condition. Thus the robot globally is more appreciated by the student in terms of objective measures while based on subjective results, we can see that implicitly it led to the formation of the same attitude formation level which means that we end up with the same positive convictions about science learning even if we consider a human as a persuasive message source However, it is not guaranteed that we will have the same level of error quotient (because it was not the case based on the data's experiment).

**Hypothesis 3: Interaction Effect (Student's Profile) X (Persuader's agency)**

Based on the tables 7.28 7.22, we can say that there were significant statistical differences for the different resulting conditions of the second experiment's design which can be described as follows (persuader's agency X the student's profile).
Pairwise comparisons are applied too in tables 7.23 7.24. Blue color prevailed in the tables 7.23 and 7.24 indicating that there are many statistically signficant results. However, there were no statistical differences in terms contrast values related to the following constructs:

- IAT: when we shift the persuasive message's source from the box to the robot. No change in implicit convictions whether it is a box or a robot.
- trust, pleasure, credibility, IAT and likeablity: when we shift the persuasive message's source from the robot to the human.
- IAT: when we shift the persuasive message's source from the box to the human. No change in implicit convictions whether it is a box or a human.
- cognitive dissonance : when we shift the persuasive message's source from the baseline to the box or the box to the human. No change in implicit convictions.

When we compare tables 7.33, 7.26 and 7.27, we can see that relational students are more sensitive in a positive way in comparison to the untilitarian students when the persuasive message is spoken by a robot rather than the baseline condition and by the human rathan than the baseline. Using a box rather than nothing as a persuasive message source seems to be more convincing for relational students rather than utilitarian ones (IAT: (+)0.41. Most importantly, when the persuasive message source is shifted from the robot, it looks like there are no special differences between relational and utilitarian students contrast values in terms of trust, pleaure, credibility and IAT with relational and utilitarian having the same evolution's tendency while we can see that it is mostly a negative evolution's tendency except for the IAT that seem to increase slightly for both groups. A comparison between both contrast group values when the persuasive message source shifts from the robot to the human shows that utiitarian students seem to be more sensitive with a negative evolution mode in terms of arousal, likeability and dominance in comparison to relational students. So, utilitarian students seem to be less aroused and less dominant and found the human less likeable when the persuasive message source is the human while in terms of perceived intelligence and cognitive dissonance relational students seem to found the human less intelligent than the robot and they got less trigerred cognitive dissonance in comparison to utilitarian students that have the same tendency too. If we consider the comparison of the shifting from the robot to

the human for both groups (utilitarian and renational students) and baed on table 7.29, we can see that there were higher contrast values for relational rather than utilitarian students in terms of dilemma levels (Nbtimesmousemovesbwexercises, Nbtimelooksbwexercises), while there are no special differences in terms of FAfterMSGisdelievered, FwhenMSGdelivered and Errorquotient contrast values which means that relational people get more in dilemma when the human is the persuasive message source, however and after all the variable that shows that the exercise is done or not after this dilemma has the same level of contrast values indicating that after all there were no special differences on the final decision taken even if the process that both groups go through is a bit different.
If we compare the situation when we use a persuasive message source rather than nothing (tables 7.30 7.31), we can see that using a persuasive message source is better and that relational students are more sensitive to the shifting from no message source to one of the three proposed persuasive message sources (the human, the robot or the box.)
Based on the tables 7.32 and 7.33, we notice that relational students are more sensitive whether during the active attitude change process (FAfterMSGisdelievered, FwhenMSGdelivered, Nbtimelooksbwexercises) or when the decision is taken to redo the wrong exercise (Errorquotient) when the persuasive message is changed from the box to a robot and from the box to the human (except for the construct Nbtimelooksbwexercises).

## 7.13 Conclusion

We conducted an experiment with the objective to verify whether people who has a difficulty with positive emotions formation (utilitarian students) and people who spontaneously choose to trigger their bad habits because they have no planned behavior on the moment of choice but they choose their behaviors spontaneously while activating unintentionally the automatic processing, can keep on interacting with the robot if some breakdowns occur during the interaction. For this purpose, we drew a similar experimental setup where we want to investigate whether there were special differences between the relational and utilitarian people, whether using a persuasive message source rather than the robot could lead to higher persuasiveness, whether proposing the message during gamma window is better and whether there were special interaction effects when we shift from one persuasive message source to another if we take into account the user's profile. It is just that instead of verifying whether people will keep interacting with the robot, we verify whether students keep on doing a difficult task once they are stricken by the cognitive dissonance. The cognitive dissonance that it is assumed to arise as well when the non expert trainer finds out that his preconceptions about the previously established communication protocol are defeated by a

robot's behavior that it is different than expected.
Results show that globally relational people scored high whether in terms of subjective or objective constructs, that proposing a message during gamma window is better than before gamma window which is better than after gamma window and proposing a persuasive message source is better than nothing (baseline). Also, we found that strikingly there were a preference for the robot by Tunisian students then comes the human, after that the box and finally we have the baseline. Based on the interaction effect results analysis, it is clear that in terms of subjective constructs, when we start to use rather than the box relational students seem to attribute higher values to the robot rather than utilitarian students, however, relational students seem to report higher arousal, pleasure and implicit positive attitude formation than the relational students. Shifting from the box to the human as a persuasive message source reveals that relational students are more sensitive to such shifting while always is it that relational students are more sensitive than utilitarian students if we shift from the baseline to the robot, box or the human.
Shifting from the robot to the human as a persuasive message source seems to lead to a more sensitivity for utilitarian students with a negative evolution in terms of arousal, dominance and likeability, while in terms of perceived intelligence and cognitive dissonance it is relational students who have higher contrast values and still many other subjective constructs seem to have so special differences whether we considerate the human or the robot as a persuasive message source. In terms of objective measures, shifting from the robot to the human seems to lead to no special contrast differences in terms of number of frames the user looks to the persuasive message source whether during the message reception (FwhenMSGdelivered) or after the message reception (FAfterMSGisdelievered), the dilemma seem to be felt more by relational students (Nbtimesmousemovesbwexercises, Nbtimelooksbwexercises), however in terms of decision taking (Errorquotient) no special differences exist when we shift from the robot to the human. Consequently, if we want to maximize the chances of keeping on doing something difficult (doing a difficult exercise or interacting with a robot that makes errors), having a persuasive message source during gamma window is better and this persuasive message can be a robot if we suppose that a human that it is available for the user to speak a persuasive message could be difficult to achieve while there will be more dilemma for relational students during the active attitude change and the possibility that a decision to redo the difficult task will be the same for both types of people (utilitrian or relational). It could be that in such case relational students will feel more cognitive dissonance and that the robot came at the proper time (more intelligent) to save them from this difficult moment if the robot is the persuasive message source rather than having a human that speaks the persuasive message. However, always on the same context, utilitarian students seem to

be more engaged with a robot (arousal, dominance) rather than a human as a persuasive message source which leads to higher likeability to the robot rather than the human.

# Chapter 8

# Conclusion

In the first chapter, we gave a brief introduction where we highlighted the importance of using behaviors that make the robot sociable so that it can be easily integrated in the society. We highlighted as well that our work involves non-expert trainers that do the dynamic scaffolding with minimally designed robots. We highlighted that the main first challenge in this case consists in finding a way to grant the robot with the capability to act autonomously. As we are interested in ecological robotics, we managed to conduct a human-human experiment to verify the redundant patterns which lead to the formation of a communication protocol. We showed that the process is incremental and leads to the emergence of agreements and disagreements about the common communication patterns. The first human knocks on the table to express his desire to make the robot moves right, left, forward or back and another human located in another room tries to translate these knocking patterns based on his interaction experience that it is formed online while interacting with the knocker. Based on the analysis of the data, we could have proposed an actor critic architecture that helps on building a smooth communication protocol. This architecture is built, integrated on the robot and tested out while we remarked that the robot succeeded when acting using this architecture to build communication protocols that are customized to the human-robot pairs.
However, there were a main problem when the robot is abandoned for a long period and then used by the non-expert trainer. The latter thinks that he is correct while assigning the instructions and that the robot should have tried to remember properly the previously established communication protocol (PECP). However, the problem was related to the human who does not pay attention to the teaching quality and forgets the rules of interaction. As the robot was taken as a scapegoat unintentionally and that a robot protesting by saying to the human he is the wrong party could be threatening for the human's social face, we proposed to use an implicit method that may trigger the human's memory to easily remember the previously encoded (during the first interaction's instance) communication rules. We used inarticulate

utterances (IUs) that may play the role of audio icons facilitating the memorization of the interaction context if synchronized with the interaction's context and maintained during the reuse of the PECP. In such a case, in a second interaction's instance after a period of robot's abundance, the robot has just to generate an IU when a special instruction is given by the human to announce the code of the robot's behavior that it is about to be executed. If the action is correct the human will not react but if the robot's action that it is about to be executed is incorrect then the human has to remember the right instruction or at least knows that the action that it is about to be executed is related to another robot's behavior. Such a method has brought about better remembrance of the PECP. We highlighted that proposing a different version of IUs during the PECP recall leads to worse performance and that proposing a variation repeat technique in a way that for each robot's behaviors we will have a dataset of IUs leads to a mediocre performance.

However, to be sure that the human will be cooperative enough to pay attention to the rules that he is forming, a minimum level of positive emotions should evolve while interacting with the minimally designed robot. Initially, we measured only the attachment that could evolve between the human and the robot. But, we remarked that the adaptation and friendliness scored low which indicates that IUs should be synchronized with the robot's visible behaviors (Vbs).

As the social bonding involves four factors (belief, commitment, involvement and attachment) rather than only the attachment, we shifted our goal to the creation first of a tool that could help measuring the social bonding more appropriately.That it is why, we created a special tool that may help us to asses the social bonding that could evolve during the HRI by taking into account the four factors. We tested it in a context where the robot is synchronizing his IUs with his Vbs and we expected that social bonding would increase just like in the child-caregiver scenario where they synchronize the most used IUs and the baby's behaviors. Results were encouraging and indicate that social bonding increases when the robot is synchronizing the IUs with the Vbs. As the results were compatible with the results that a caregiver could achieve while interacting with a baby, we intended to use our validated tools in a case study where we have to make the choice between designing a minimally designed robot that it is proactive or reactive. Knowing whether we have to conceive a proactive or reactive robot is of great use because we can determine how can we boost the social bonding by keeping the same robot's behavior and only program some initiatives that may make the robot looks like proactive. If some initiatives could have a positive influence on the social bonding, then all what we have to so is just to program some initiatives in the minimally designed robots to increase the social bonding felt by the human during the HRI. The results indicate that conceiving a minimally designed robot that is proactive is better than designing

a minimally designed robot that it is reactive.
While doing the experiment about the social bonding, we remarked that a very small proportion of the participants do not feel social bonding. By applying the PPI-R, we remarked that these participants are a bit coldhearted. And thus, we deduced that for some of the cold-hearted (or what we call utilitarian)students it is difficult to have a proper cooperation with the robot that uses IUs during the interaction. In fact, these utilitarian people have some trouble on evolving positive emotions in general. It is true that we could not report this claim based on data because of the few proportion of people that has these problems of social bonding evolvment absence, however in [136] Zadeh et al, highlighted the same issue and indicates that people who are cold-hearted have a problem on interpreting and responding to another party's inarticulate porosody.
Consequently, we assumed that such people who are utilitarian could feel better engaged during the HRI if a persuasive message could be generated when an error occurred during the HRI. As an example, we can say a robot that makes errors while reusing a PECP just like in our case. Such breakdowns could be annoying for utilitarian people and since they cannot process the inarticulate prosodic information, we though that a message influencing them to continue using the robot even if some breakdowns occur could resolve the problem. Such a persuasive message could also be influencing for impulsive relational students who use their automatic processing when they are in difficulty and call upon their stored attitudes from the cognitive miser. If the triggered attitudes are negative the human might feel like he wants to abandon the robot even if consciously or in a proper way in his planned behavior intentions he said that he can keep interacting with such a robot that it is making errors (according to his thinking because after all in the case of PECP reuse, it is the human who is making errors).
To propose a persuasive message, we should take into account different parameters and we should pay attention to the concept of cognitive dissonance that it is tightly coupled with the persuasiveness paradigm. One of the main points that one can mention, when we talk about cognitive dissonance is the gamma window. Gamma window is a period of time that it is characterized by a cognitive and emotional dilemma that leads the human to adopt a counter attitudinal behavior to resolve the dissonant concepts. There are some parameters that should be there if we want to mention that cognitive dissonance might occur (which we call in our study as pivots: cognitive closure, foreseeable consequences, etc..) which need to be measured. After that comes the choice of the moment during which the robot could deliver a persuasive message. Based on our experiments, the best moment is during the gamma window. Now, there are plenty of persuasive message techniques. In our study, we chose "that's not all technique" while more techniques could be tested out in future work

to see whether there are some differences. We also, highlighted in our experiment that relational students scored high in terms of objective and subjective results and that using a robot is the best solution in order to persuade the person to continue doing a task that it is difficult (such as redoing a a difficult exercise or interacting with a robot that makes multiple errors) whether he is relational or utilitarian.

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