



# Generating Proactive Communicative Robot Behaviors

Sera Buyukgoz

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ÉCOLE DOCTORALE SMAER(ED 391)  
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THÈSE DE DOCTORAT

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# Generating Proactive Communicative Robot Behaviors

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# *Abstract*

Proactive behaviors are self-initiated behaviors to cope with a problem that has or will occur. Humans are proactive; if you drop something in front of another human, it is likely that they would pick it up for you. Currently, while great advances have been made in robotics and human-robot interaction (HRI), the issue of designing robots to generate proactive behaviors remains an open challenge. Proactivity is not to be confused with reactivity; while proactive behaviors are self-initiated, reactive behaviors are the result of a command triggered from the user. In order for robots to be truly assistive to humans, we need the robot to be equipped with proactive (and not just reactive) behaviors; as it can help humans to achieve their goals. It has often become the case that a robot and a human might share the same physical environment but not interact, leaving the human unaware of the robot's capabilities. It is thus desirable that robots have proactive behaviors and can take initiative during the interaction, as it may improve the interaction quality and satisfy the user's desires. One of the issues unaddressed with current research on proactivity is that there is no clear definition of what makes a robot proactive. Studies have so far focused on proactive behaviors very specific to one domain, i.e. neglecting a general framework or model of proactivity that could be used in a wide variety of HRI scenarios.

In this thesis, we address the issue of proactivity from the perspective of a robot assisting a user, with a focus on the intentions of the user to achieve a goal. We specifically focus on the reasoning over these intentions, of 1) when proactivity could occur, and 2) what proactive behaviors to generate in this interaction. To do so, we propose a generic cognitive framework that encompasses an entire interaction between the user and the robot. Then we specify within this framework, our reasoning module of when and what proactive behaviors to instantiate. To propose such a framework, we address the challenges of user intention recognition, reasoning over these intentions, and then generating appropriate proactive behaviors.

We propose novel methodologies for our framework to generate proactive robot behaviors: i.e. recognizing human intentions by inverse planning and reasoning over these intentions by rule-based algorithms. Lastly, since we utilize a humanoid robot, we choose to focus on the generation of communicative proactive behaviors. To summarize, the proposed framework aims to detect the problems that a user could face based on their current inferred intentions, and then plans a trajectory of proactive actions the robot could undertake to help the user to achieve their goal.

To evaluate our proposed framework, we first applied it to a recipe creation task, where the goal of the user was to create a recipe, and the robot's goal was to proactively help the user to achieve this task. The results of our pilot study indicated that when the robot was too proactive, users tended to create less novel recipes. In a detailed study, we found that the frequency (i.e. when and how often) of the robot initiating proactive behaviors is crucial, and there are strong links between the proactivity of the robot and the creative output of the user. These results solidified that our generic proposed framework can be applied to different settings, and while there is the correct recognition of intent and appropriate generated behavior, the frequency of the initiated proactive behaviors could be improved. Our second application combines our reasoning module with the latest state-of-the-art framework on proactivity, i.e. equilibrium maintenance. We do so in order to improve the frequency and appropriateness of communicative proactive behaviors initiated by the robot. We evaluate this framework on a home assistant task, where the robot's goal is to proactively assist the user in their everyday needs. These results indicate that the



proposed framework is flexible enough to combine with already existing solutions to have improved proactive reasoning.

Thus in this thesis, we propose some strategies to make robots more proactive, specifically for assisting a user. Future work could expand the framework proposed with self-directed proactive behaviors for the robot itself.

**Keywords:** Proactive Behavior, Human-Robot Interaction, Goal Planning, Behavior Generation, Human Intention Recognition, Intention reasoning, Creative Robot

## Résumé

Les comportements proactifs sont des comportements auto-initiés pour faire face à un problème qui s'est produit ou se produira. Les humains sont proactifs; si vous laissez tomber quelque chose devant un autre humain, il est probable qu'il le ramasse pour vous. Actuellement, alors que de grands progrès ont été réalisés en robotique et en interaction homme-robot (HRI), la question de la conception de robots pour générer des comportements proactifs reste un défi ouvert. La proactivité ne doit pas être confondue avec la réactivité ; alors que les comportements proactifs sont auto-initiés, les comportements réactifs sont le résultat d'une commande déclenchée par l'utilisateur. Pour que les robots soient vraiment utiles aux humains, nous avons besoin que le robot soit équipé de comportements proactifs (et pas seulement réactifs) ; car il peut aider les humains à atteindre leurs objectifs. Il est souvent devenu le cas qu'un robot et un humain partagent le même environnement physique mais n'interagissent pas, laissant l'humain inconscient des capacités du robot. Il est donc souhaitable que les robots aient des comportements proactifs et puissent prendre des initiatives lors de l'interaction, car cela peut améliorer la qualité de l'interaction et satisfaire les désirs de l'utilisateur. L'un des problèmes non résolus par les recherches actuelles sur la proactivité est qu'il n'y a pas de définition claire de ce qui rend un robot proactif. Les études se sont jusqu'à présent concentrées sur des comportements proactifs très spécifiques à un domaine, c'est-à-dire en négligeant un cadre général ou un modèle de proactivité qui pourrait être utilisé dans une grande variété de scénarios HRI.

Dans cette thèse, nous abordons la question de la proactivité du point de vue d'un robot assistant un utilisateur, en mettant l'accent sur les intentions de l'utilisateur pour atteindre un objectif. Nous nous concentrons spécifiquement sur le raisonnement sur ces intentions, de 1) quand la proactivité pourrait se produire, et 2) quels comportements proactifs générer dans cette interaction. Pour ce faire, nous proposons un cadre cognitif générique qui englobe toute une interaction entre l'utilisateur et le robot. Puis nous spécifions dans ce cadre, notre module de raisonnement de quand et quels comportements proactifs instancier. Pour proposer un tel cadre, nous abordons les défis de la reconnaissance des intentions de l'utilisateur, du raisonnement sur ces intentions, puis de la génération de comportements proactifs appropriés.

Nous proposons de nouvelles méthodologies pour notre framework afin de générer des comportements de robots proactifs : c'est-à-dire reconnaître les intentions humaines par une planification inverse et raisonner sur ces intentions par des algorithmes basés sur des règles. Enfin, puisque nous utilisons un robot humanoïde, nous choisissons de nous concentrer sur la génération de comportements communicatifs proactifs. Pour résumer, le cadre proposé vise à détecter les problèmes auxquels un utilisateur pourrait être confronté en fonction de ses intentions déduites actuelles, puis planifie une trajectoire d'actions proactives que le robot pourrait entreprendre pour aider l'utilisateur à atteindre son objectif.

Pour évaluer notre cadre proposé, nous l'avons d'abord appliqué à une tâche de création de recette, où le but de l'utilisateur était de créer une recette, et le but du robot était d'aider proactivement l'utilisateur à accomplir cette tâche. Les résultats de notre étude pilote ont indiqué que lorsque le robot était trop proactif, les utilisateurs avaient tendance à créer des recettes moins originales. Dans une étude détaillée, nous avons constaté que la fréquence (c'est-à-dire quand et à quelle fréquence) le robot initie des comportements proactifs est crucial, et qu'il existe des liens étroits entre la proactivité du robot et la production créative de l'utilisateur. Ces résultats ont confirmé que notre cadre générique proposé peut être appliqué à différents contextes, et bien qu'il

y ait une reconnaissance correcte de l'intention et un comportement généré approprié, la fréquence des comportements proactifs initiés pourrait être améliorée. Notre deuxième application combine notre module de raisonnement avec le dernier cadre de pointe sur la proactivité, c'est-à-dire le maintien de l'équilibre. Nous le faisons afin d'améliorer la fréquence et la pertinence des comportements communicatifs proactifs initiés par le robot. Nous évaluons ce cadre sur une tâche d'assistant à domicile, où l'objectif du robot est d'aider de manière proactive l'utilisateur dans ses besoins quotidiens. Ces résultats indiquent que le cadre proposé est suffisamment flexible pour se combiner avec des solutions déjà existantes afin d'avoir un raisonnement proactif amélioré.

Ainsi dans cette thèse, nous proposons quelques stratégies pour rendre les robots plus proactifs, spécifiquement pour assister un utilisateur. Des travaux futurs pourraient élargir le cadre proposé avec des comportements proactifs auto-dirigés pour le robot lui-même.

**Mots-clés :** Comportement proactif, Interaction homme-robot, Planification d'objectifs, Génération de comportements, Reconnaissance de l'intention humaine, Raisonnement d'intention, Robot créatif

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# List of Abbreviations

<b>ANOVA</b>	<b>AN</b> alysis <b>O</b> f <b>V</b> ariance
<b>API</b>	<b>A</b> pplication <b>P</b> rogramming <b>I</b> nterface
<b>BDI</b>	<b>B</b> elief <b>D</b> esire <b>I</b> ntention
<b>DIY</b>	<b>D</b> o <b>I</b> t <b>Y</b> ourself
<b>EQM</b>	<b>E</b> Q <u>u</u> ilibrium <b>M</b> aintenance
<b>GUI</b>	<b>G</b> raphical <b>U</b> ser <b>I</b> nterface
<b>HCI</b>	<b>H</b> uman- <b>C</b> omputer <b>I</b> nteraction
<b>HIRR</b>	<b>H</b> uman <b>I</b> ntention <b>R</b> ecognition <b>R</b> easoning
<b>HRC</b>	<b>H</b> uman- <b>R</b> obot <b>C</b> ollaboration
<b>HRI</b>	<b>H</b> uman- <b>R</b> obot <b>I</b> nteraction
<b>MDP</b>	<b>M</b> arkov <b>D</b> ecision <b>P</b> rocesses
<b>MOMPD</b>	<b>M</b> ixed <b>O</b> bservability <b>M</b> arkov <b>D</b> ecision <b>P</b> rocesses
<b>OWL</b>	<b>O</b> ntology <b>W</b> eb <b>L</b> anguage
<b>PiM</b>	<b>P</b> arallel <b>i</b> ntegration <b>M</b> ethod
<b>PDDL</b>	<b>P</b> lanning <b>D</b> omain <b>D</b> efinition <b>L</b> anguage
<b>RDF</b>	<b>R</b> esource <b>D</b> escription <b>F</b> ramework
<b>SD</b>	<b>S</b> tandard <b>D</b> eviation
<b>SiM</b>	<b>S</b> equential <b>i</b> ntegration <b>M</b> ethod
<b>TFVT-HRI</b>	<b>T</b> rans <b>F</b> ormer with <b>V</b> isual <b>T</b> okens for <b>H</b> uman- <b>R</b> obot <b>I</b> nteraction
<b>ToM</b>	<b>T</b> heory of <b>M</b> ind
<b>UEQ</b>	<b>U</b> ser <b>E</b> xperience <b>Q</b> uestionnaire
<b>WoZ</b>	<b>W</b> izard of <b>O</b> z
<b>XAI</b>	<b>E</b> Xplainable <b>A</b> I



*Dedicated to Future...*



## Chapter 1

# Introduction

*'A robot should not, through inaction, allow a human to come to harm.'*

Isaac Asimov

### 1.1 Motivation

Robots and humans living together and benefiting each other is a long lasting dream ever since the stories of Asimov. Asimov defines three laws that are still valid for defining interaction between robots and humans. In the three laws of Asimov, the first law - "*A robot should not, through inaction, allow a human to come to harm.*" - highlights the importance of being proactive to protect humans (Bremner et al., 2019). In this thesis, the focus is the autonomy of the robot in taking initiative during the interaction as proactivity of the robot.

The majority of researcher working on social robots, are working for capability of the robot that could share the same environment with humans. Social skills are believed to be the key of living together. However, the creation of social robots is not as easily achievable as in science fiction. The term *social robot* stands for an autonomous robot that has the ability to interact and communicate with other agents (human or robot), where the term focuses on human-like social skills. The robot's sociability defines as the robot proactively engaging with humans (Breazeal, 2003). Not only that, to be considerate, **proactive** and non-intrusive is stated as the important characteristics of a social robot (Dautenhahn, 2007). Where the **proactivity** defined as taking initiative whenever it is necessary to support humans for their desires or intentions (Dautenhahn, 2007). Resulting from this definition, proactive robot behavior is an essential aspect of human robot interaction (HRI) where the robot is able to initiate an intervention to help the human (Ali et al., 2009). Further, acting voluntarily in a way to benefit humans is also known as pro-social behaviors (Paiva et al., 2018). That means proactive behaviors fosters pro-social behaviors.

Pro-social behaviors are promoted as an essential part of social robots. Since majority of the robots achieve any goal in one way or another, however, reasoning about a human's mind and acts according to it in a unstructured environment remains a challenge. The positive effect of the pro-social behavior can clearly be seen in examples of social dilemmas (Correia et al., 2019). The main questions that are still remaining are about how the robot can detect if a human needs the robot's pro-sociability?

In this thesis, we foster pro-sociality via proactive behaviors. The value of proactive robot behavior lies in reducing the cognitive load of the human. The robot's ability to determine its own action liberates the human from constantly watching the robot and giving proper commands on the right time. Let's consider Wizard of Oz (WoZ) studies. In WoZ studies, there is always a controller, who observes and decide



Human Action	Related Concept:	Robot
User is in the room	Situation assessment:	A person is detected near the robot
User collecting its own things	Intention Recognition:	User goes to lunch
	Context Awareness:	The robot knows that to go to lunch, User needs to leave the building and cross the playground.
	Problem Detection:	The robot knows that if anyone will be wet in rain, that will be a problem.
	Solution Awareness:	The robot knows that Umbrella is used to avoid the problem of getting wet in rain.
	Environment Knowledge:	The robot knows that there is Umbrella in the classroom.
	Situation Awareness:	The robot knows that it is raining or going to rain "today".
User did not take an umbrella	Situation Assessment:	The robot knows user will get wet
	Theory of Mind:	The robot assumes the user did not know it will rain
User will get an umbrella	Proactive behavior generation:	Robot warns user about the rain

TABLE 1.1: Dummy Interaction between Human and Robot to show the necessary modules. Human column represents the user's action that is achieved or will be achieved in the environment. Robot column shown the robot's reasoning as a result of related concept.

an action for the robot. In contrast to that, in autonomous studies, the robot decides its action on its own. Most of the time, they are acting to respond to situational cues, which is also defined as reactive behavior. On the other hand, proactive behaviors are taking initiatives to enact an action to be beneficial for the human, that is the self initiating nature of the behavior, which causes acting in advance autonomously (Grant and Ashford, 2008).

In the scenarios where the robot share the same environment with the human especially with non-expert humans show that robots are still not ready to be part of daily life as a social assistant. The interaction with non-expert humans are always challenging. The challenge lies in how to choose a strategy to communicate with them. Let's give an example of an interaction to overview which features is needed to be proactive in Table 1.1.

As it is shown in Table 1.1, in order to generate proactive behavior of the robot, it is clear that understanding of the situation, human's mental state and environment are some of necessities for anticipation of future changes. In this thesis, the highlighted term is the proactive communicative robot behavior that fosters pro-social behaviors. The proactive behavior aims to improve a robot's autonomy and ease of living

together with a human. However, within the studies which presents proactive robot behavior, there is no agreement on clear definition or methodologies to define proactive robot behaviors. From this motivation, in this thesis we generate proactive communicative robot behavior from a knowledge based systems.

## 1.2 Definition of the concepts

In this section we define the concepts that will be encountered through out the thesis. Some of those terminologies are used in various meanings in the human-robot interaction domain.

- **Agent** represents the individual either human or robot that are capable of performing an action.
- **Action** is an observable process that an agent alters its environment.
- **Behavior** is an observable response that made out of action(s) to a situation.
- **User** is an individual that is interacting or using the tool.
- **Participant** is an individual human that is participating to the experiment.
- **Task** is used for defining the overall interaction including the game or event that the user is exposed with the robot.
- **Goal** is used for defining individual small achievements in the task. The same task could have more than one goal.
- **Intent** or **Intention** are used for defining the user's commitment to a goal that will achieve.
- **Knowledge** is defined as a set of multiple information. It includes social rules, ground truths, agent's beliefs, conditions of involuntary environmental changes and actions of the agents (robot and human).
- **Collaborate** is working together with human on a shared goal.
- **Cooperate** is working together with human to achieve the human goal.

## 1.3 Problem Statement

In this thesis we consider scenarios where the robot and the human are sharing the same environment. If the robot observes that the human is about doing something wrong, then the robot should be able to intervene without being asked. This type of pro-social behavior of the robot is aimed to tackle with proactive communicative robot behavior. The *proactive communicative robot behavior* can solve this problem by taking an initiative to be beneficial for the human. In this thesis, we focus on the problems of (i) how to generate the proactive robot behavior, (ii) when and what proactive robot behavior could occur.

## 1.4 ANIMATAS

The research in this thesis was conducted as a part of the European Union - Horizon 2020 (H2020) Innovative Training Network(ITN) project called ANIMATAS<sup>1</sup>. ANIMATAS<sup>2</sup> stands for advance intuitive human-machine interaction with human-like social capabilities for education in schools. For this purpose 15 early-stage researchers (ESR) conducted research on three main research topics: 1. Perception, 2. Social learning, 3. Personalized adaptation

The research in this thesis is part of the personalized adaptation topic. This topic aims development of new tools for robots that could adapt to the humans in unstructured and dynamically evolving social interaction scenarios. We are proposing to tackle this issue with proactive robot behavior. Our contributions are focused on technical challenges of generation of the proactive communicative robot behavior might be extended in the future to more practical applications that can be used in schools. In that sense, we design an applications that can directly be used in schools (see Section 3.2) and used that knowledge to design our generic framework for generating proactive communicative robot behavior.

## 1.5 Objectives

The overall aim of the thesis is to generate proactive communicative behaviors in domain-independent manner. To achieve this goal the following objectives are proposed.

**O1:** Development of a generic framework that generates the proactive behavior of the robot.

**O2:** Evaluation of the generic framework that generates the proactive behavior of the robot.

## 1.6 Contributions

The contribution of this thesis are the following:

1. The generic cognitive framework is generated. The proposed framework generates proactive communicative behaviors depending on the knowledge it has.
2. Symbolic knowledge usage to store the relationship between objects and states. Transformation of the knowledge to planning file.
3. A human intention recognition system is developed. Recognition system uses the same planner and same definition of the environment by adapting inverse planning principles.
4. The finite state reasoning system based on predefined rules is proposed. The system reasons on human intention to trigger proactive robot behavior.
5. The proactive communicative behavior is presented in the sense of verbal communication.

<sup>1</sup>For further information on the project please frequent the web site at <http://www.animatas.eu>

<sup>2</sup>This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 765955

6. Intention based proactive behavior generation is combined with predictive based proactive generation framework; equilibrium maintenance from (Grosinger et al., 2019). The integrated framework aims to broaden to generate appropriate proactive behavior.
7. An educational task is defined to highlight the physical presence of robot where teaching multiplication of abstract numbers.
8. Communicative proactive robot behaviors are evaluated on the task of creativity. The similarities of proactive and creative behaviors are presented.

## 1.7 Outline

The rest of the thesis is outlined by following chapters divided under the three main parts.

**Part I:** Summarizes the state of the art and our pilot experiment for educational task that will indicate the need of proactivity.

- **Chapter 2** presents the state of the art of research on proactivity and the areas related to proactivity. These are theory of mind, belief-desire-intention framework, human intention recognition, and planning.
- **Chapter 3** discusses the latest educational methods and relationship with proactive robots. MobiAxis, an educational task is introduced and reports with the results of pilot study.

**Part II:** Encapsulates the proposed architecture to define the trials of proactive behavior generation in detail

- **Chapter 4** introduces the proposed rule-based framework to generate proactive communicative robot behavior based on human intention reasoning.
- **Chapter 5** introduces the framework that merge intention-based proactivity (from Chapter 4) and predictive based proactivity (from Grosinger et al. (2019)).

**Part III:** Reports the experiments that were done to evaluate the proposed framework.

- **Chapter 6** introduces the pilot study.
- **Chapter 7** introduces the study that proactivity and creativity assessed with rule based proactive generation model.
- **Chapter 8** introduces the study that intention based proactive generation model merged with predictive based proactive behavior generation model.
- **Chapter 9** concludes the thesis by summarizing the framework, evaluating the objectives, discussing the proposed system on generating proactive robot behavior in technical and behavioral aspects, listing limitations of the framework, and pointing out the future works that could build upon presented work.

## 1.8 Publications

The content of this thesis partially could be find in the following papers. The papers are listed by their types.

- Journal Papers

- **Buyukgoz S.\***, Grosinger J.\*, Chetouani M., Safiotti A., "Proactive Robot Acting by Reasoning on Human Intention, Preference and Prediction", *Frontiers in Robotics and AI*. (Submitted)

Part of Chapter 5 & 8

- **Buyukgoz S.**, Pandey A. K., Chamoux M., Chetouani M., "Exploring Behavioral Creativity of a Proactive Robot", *Frontiers in Robotics and AI*. 8:694177. DOI: 10.3389/frobt.2021.694177. November, 2021

Part of Chapter 7

- Workshop Papers

- **Buyukgoz S.**, Chamoux M., Pandey A. K., Chetouani M., "Exploring Proactivity aspect of Creativity in Human-Robot Interaction", *The 12th International Conference on Social Robotics (ICSR 2020), Workshop on Creativity and Robotics*, Golden, Colorado. November, 2020.

Part of Chapter 6

- Tatarian K., Wallkoetter S., **Buyukgoz S**, Stower R., Chetouani M., "MobiAxis: An Embodied Learning Task for Teaching Multiplication with a Social Robot", *IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), R4L Workshop*, New Delhi, India. October, 2019.

Part of Chapter 3

- Late-Breaking Reports

- **Buyukgoz S**, Chetouani M., Pandey A. K., "Towards Automatic Synthesis and Instantiation of Proactive Behaviour", *IEEE International Conference on Robot and Human Interactive Communication (RO-MAN), Late-Breaking report (LBR)*, New Delhi, India. October, 2019.

Part of Chapter 4

## **Part I**

# **Related Work & Pilot Study**



## Chapter 2

# Background

### 2.1 Introduction

This chapter is divided into two parts. In the first section (see section 2.2), we give a general overview of proactivity. To do so, we firstly define proactivity according organizational psychology. Then, we show the intersection with the state-of-the-art definitions used in robotics.<sup>1</sup> Given the definitions, we discuss the difference between proactive and reactive behaviors (see subsection 2.2.1), and why a robot equipped with only reactive behaviors is less desirable than one equipped with proactive behaviors.

In the section 2.3, we formalize the generation of proactive behavior in robotics. To generate proactive behaviors in a robot, it is necessary to create a model of the human's mental state. Thus, we firstly the literature in HRI related to the generation of proactive behaviors (see section 2.3). Then, we focus on outlining two theoretical models to represent the human that could be used to generate appropriate proactive behavior: i) *Theory of Mind (ToM)* (see item 2.3), a cognitive theory concerned with understanding the human's mental state and ii) the *Belief-Desire-Intention (BDI)* model (see item 2.3), a computational model that relies on ToM to reason about the human's intentions. Reasoning about intentions using BDI provides a link between the actions a human takes in the environment, and their corresponding mental state.

### 2.2 What is Proactivity?

Proactivity is a widely used term but does not have a standard definition. Several definitions used in HRI are borrowed from the organizational psychology domain. In robotics, proactivity is generally thought of as a robot taking initiative during an interaction, without explicit instructions from the human. Grant and Ashford (2008) define proactive behaviors in humans as “anticipatory, change-oriented and self-initiated” behaviors, which most closely aligns with proactivity as studied in this thesis. In the following paragraphs, we give an overview of how the definitions of proactivity have changed.

**Organizational psychology** In robotics, several definitions of proactivity have been adapted from the domain organizational psychology. Whitely and Blankfort (1933) initially used the term to refer to learning from past experience. Page and Page (2003) then shifted the stress from learning, to taking responsibility and being aware of one's actions. Merriam-Webster (2020) currently defines proactivity as “acting in anticipation of future problems, needs or changes”. From organizational psychology,

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<sup>1</sup>Note, some of the works discussed may not explicitly use the term “proactivity”, but are considered in this thesis given our definitions of proactivity.



the current accepted notion of proactivity refers to humans' anticipatory, change-oriented and self-initiated behaviors (Grant and Ashford, 2008).

Even from an evolutionary perspective, it is advantageous for humans to be proactive. For example, if A leans towards B to give B an object, B may lean towards the object to reach it. This *action* B takes (leaning towards the object) reduces the effort A has to take to give the object. This action stems from B's awareness of A's *mental state*, resulting in helping A achieve the *goal* (to give B the object). Proactivity hence results from a *perception of the other's mental state*, known as *Theory of Mind* (see item 2.3). Tomasello et al. (2005) claimed that humans have the ability to predict the other's actions and consequences resulting from this mental state. Proactivity is present even in infancy, with Warneken and Tomasello (2006) showing that 18-month-old infants are capable of exhibiting proactive helping behavior. Thus, proactivity is an inherent characteristic of humans (Grosinger et al., 2019), though it is not easy to identify these specific characteristics. Grant and Ashford (2008)'s definition as stated (anticipatory, change-oriented and self-initiated) is an aggregation of several definitions of proactivity in this domain.

**Robotics** Taking from Grant and Ashford (2008), many of the recent works in robotics generally define proactivity (of the robot) as an anticipatory action initiated by the robot to impact itself or others (see Peng et al. (2019) and Kraus et al. (2021) and so on). A reduced definition of this, is for the robot to simply *act before it is requested* (C. and Chodorowski, 2019). Grant and Ashford (2008) say that proactive behavior could be concerned with being proactive for oneself, being proactive for others, and being proactive for the community. Despite the definition being simple, proactive behavior could be varied, and in robotics this general notion is difficult to adapt. Here are some studies in HRI that are varied in terms of generated proactive behavior:

1. *Anticipation of human needs.* Here, the robot understands the human's needs and offers its support to clarify confusion (Pandey et al., 2013), provide suggestions (Peng et al., 2019; Baraglia et al., 2016; Myers and Yorke-Smith, 2007; Bader et al., 2013; C. and Chodorowski, 2019), anticipate possible failures and plan repair (White et al., 2015), or prevent future hazards (Bremner et al., 2019).
2. *Initiate own goal.* Here, the robot assesses the environment to initiate its own goal (Grosinger et al., 2016; Zhang et al., 2015).
3. *Improvement of the robot's knowledge* Here, the the robot may ask the human for validation or for the human to identify gaps in the robot's knowledge (Lemaignan et al., 2010; Moulin-Frier et al., 2017; Garrell et al., 2013).
4. *Seeking engagement and interaction.* Here, the robot may proactively seek human for interaction (Garrell et al., 2013) or try to continue the interaction (Liu et al., 2018).
5. *Adaptation to the human.* Here, the robot may adapt to the human's action while working together (Awais and Henrich, 2012), or while serving the human (Fiore et al., 2015). The robot may consider the human's habits and adapt as to not become annoying (Rivoire and Lim, 2016) or to be more human like (Cramer et al., 2009; Han and Yanco, 2019).
6. *Adaptation of the role.* Here, the robot may change roles from leader to follower, for example during cooperative manipulation tasks (Bussy et al., 2012; Thobbi et al., 2011).

Thus, while the definition of proactivity is broad, when applied to HRI, proactivity of the robot is an *application-by-application based behavior*. Thus depending on the context, the required proactive behavior changes and becomes more specific to the needs of the application. That is why there is no complete agreement on the definition. All of these could be considered under the definition of proactivity.

### 2.2.1 Proactivity versus Reactivity

It is important in HRI to distinguish proactive behaviors with reactive behaviors, as they are both types of behaviors that could be initiated by the robot. While proactive behaviors are defined as actions initiated by the robot *when it is needed*, reactive behaviors are defined as reacting to a situation which has *already occurred*. For example in the joint task of (Baraglia et al., 2016) where the human and the robot jointly work together in the same environment, reactive behavior was initiated in the form of a helpful action when the user explicitly asked a question. This means that the robot initiated an action (answering a question) when there was a demand. However, if the robot were to act proactively, the robot would *reason about* the user status. As a result of this reasoning, if the robot decides that the user is stuck or needs help, then, the robot would initiate an action to be helpful to the user.

While in the previous example, the demarcation between proactive and reactive behavior is clear, there are other HRI tasks where it is not. For example, depending on how the user status is evaluated, it is difficult to distinguish whether the initiated action is proactive or reactive. Hypothetically, a robot may exhibit immediate reactive behaviors to the user (such as correcting them if they took a misstep in a task), however, with the overall proactive goal of saving the user time – and hence, exhibiting reactive responses while proactively reasoning about the actions taken.

For example in the work of Peng et al. (2019) they hard-coded policies for a WoZ study to generate proactive behavior of a robot to assist a user during shopping. This work was mainly interested in finding the *right degree of proactivity*. These degrees of proactivity were classified as low (the robot provide options and ask user's opinion without having any assumptions), medium (the robot ask user's preferences according to its assumptions) and high (the robot acts according to its assumptions). The low level of proactive behavior could be considered a reactive action. Humans also preferred the proactive response (medium) compared to the reactive response.

Similarly, preferring a *moderate* level proactive behavior is shown in Kraus et al. (2021), i.e compared to reactive responses/ high level of proactivity. They define an autonomous system which creates proactive verbal suggestion in a Do-It-Yourself (DIY) scenario. The user found the high proactivity scenario (intervention) intrusive, as the robot in that context pursued the action without notifying the user. The users liked the moderate proactive actions (where the robot notified the human but did not intervene), since they felt they are in charge of the situation. Thus there is a spectrum of proactive behavior, where not only reactive actions may be considered undesirable, but also highly proactive actions could be misconstrued as intrusive.

Thus reactive behavior also could be proactive depending on the *intrinsic motivation*. Intrinsic motivation is defined as doing an action for an inherent satisfaction (of the robot) while *extrinsic motivation* is defined as doing an action for an outcome (Oudeyer and Kaplan, 2008). If we think in this way, intrinsic motivation represents proactive behavior since in our definition, proactive action is initiated to help the human and give inherent satisfaction, and not to satisfy any outcome of task. Thus, reactive behaviors could be thought of as representing extrinsic motivation, as they rely on cues of explicitly stated needs (by the user).

Therefore, proactive behavior that has an intrinsic motivation, i.e. to benefit humans. In this sense proactive behaviors can carry the motivation of being *pro-social* where the behavior of the robot that is beneficial/helpful towards the human, with the motivation of preventing the user from getting affected from discomfort that can happen in future (for example, a reminder to take an umbrella when queried about the weather).

To summarize, proactive behaviors are self-initiated behaviors. In contrast, reactive behavior is only answering to the demands of the environment without considering the future outcomes. Proactive behaviors constantly consider the future and outcomes of the actions, even when reacting to the demands.

## 2.3 Generation of Proactive Behaviors

Having given a general introduction to proactivity in the previous section, in this section, we formalize the generation of proactive behavior in robotics. There are several ways to generate proactive robot behavior, from data-driven to cognitive approaches.

Data-driven approaches train models using data collected from human-human data, where the focus is on *learning* characteristics of the data using machine learning approaches. For example, in the data-driven approach of Liu et al. (2018), a robot learns the appropriate moments to initiate proactive action and respond, from an input data-set consisting of human-human interactions. Additionally, in this work, the system keeps track of the history of the interaction to make sure the initiated action matches with the context. The limitations of data-driven approaches, as mentioned by Liu et al., 2018, is that this methodology could be applied to environments where context-dependent repeatable actions could be captured. The generalization of these methodologies to different domains remains an open problem.

Part of data-driven approaches are end-to-end frameworks, where the interpretability of the steps taken to arrive at the output is not explainable. For example, the TransFormer with Visual Tokens for Human-Robot Interaction (TFVT-HRI) model of Xue et al. (2020) uses visual cues (such as environmental objects specific to the scenario) to generate proactive behavior. The paper shows that the robot identifies social cues to learn social rules (such as greeting humans using voice when they pass by). However, as a result of end-to-end framework, the evaluation/measurement of *which* social rules were learned depending on which reasoning is not expressive. This could lead to learning an unwanted situation for example, robot could learn to block human to greet as a social rule.

Cognitive approaches focus on adaptation of cognitive theories (often taken from literature in cognitive science/psychology) to create an approach for the robot to interact with the human. Cognitive approaches can also be used to generate proactive behavior. Studies use different classification systems to address the cognitive capabilities of the agent. The vast amount of classification systems, coupled with different terminologies prevents having a clear definition of proactivity and thus a possible generic solution. Grosinger et al. (2019) uses cognitive capabilities to initiate proactive action. These capabilities are reasoning over goals, actions, plans and context. While the generation of proactive behaviors using this approach was successful, it needed well defined rules. For example all actions, goals, preferences, desirable situations need to be given to the system to achieve the desired behaviors. Thus the system could be used in well defined and controlled environments alone, as it is hard to create full-observability in the dynamic real life environment. Another example is

Moulin-Frier et al. (2017), that uses architecture that based on Distributed Adaptive Control (DAC) theory of the mind and brain (an adaptation of Theory of mind, discussed in subsequent sections). The architecture is focused on improving the robot's knowledge & seeking information as part of the proactive behavior. While the system is very well defined, it could face the same issues as the architecture proposed by Grosinger et al. (2019).

We focus on a generic methodology that could potentially incorporate hybrid approaches (data-driven and cognitive) called the *primitive cycle of intelligent agents*. This comprises of 1. Sense, 2. Plan, 3. Act phases (which we apply to proactive behavior generation). Thus, these components are as follows;

1. **Sense**; where the robot perceives the environment and reasons about it. The robots' awareness of its environment, the human and the task are perceived from sensors. This could mean the constant detection of the humans intentions and goals. Reasoning over the detected sensory data, leads to the interpretation of situations, situation assessment and situation awareness. Endsley (1995) defines this process of situation awareness into three level which encapsulates each other; first level: *Perception* of the situation, second level: *Comprehension* of the situation and third level: *Projection* of the future.
2. **Plan**; the robot should consider the need of person during interaction. Creating a better plan for to optimizing already existing one or actions that explicitly or implicitly helping effect to reach target goal.
3. **Act**; where robot initialize the action to be proactive. Incorrputibility of human analyzed to generate action.

Majority of the cognitive approaches studies generates proactive behavior by anticipating human intentions. The phenomenon of attributing other's inner state is known as Theory of Mind. Before detailing on ToM and BDI, which is a detailed computational model uses in intelligent systems. We review other cognitive models that generate proactive behavior.

### Theory of Mind (ToM)

Theory of Mind (ToM) is known as the ability of attributing other's mental state (Premack and Woodruff, 1978). (Premack and Woodruff, 1978) defines mental state as the combination of other's knowledge, intention, belief, desire, thinking, doubt, etc. Then, ToM is estimating of other's mental state from their behavior/action. In fact, several research studies have shown that attributing human's mental state by observing human's behaviors is creating chance for robot to anticipate proactive help towards human (Fiore et al., 2015; Hansen and Bolander, 2020).

The definition of ToM -prediction of agent's mental state from their behavior- is also linked with understanding perception of the agents and separating their belief from the truth (Airenti, 2015). In this regards, the false-belief experiment which is also known as 'Sally-Anne Test' presented by (Baron-Cohen et al., 1985).

Hansen and Bolander (2020) is demonstrated false-belief theory of ToM. In the system, robot proactively communicated with the user to correct their belief. While they are reasoning on the system, epistemic logic planner used to addresses ToM definition inside the planner. That means the planner was aware the mental states of all agents, in this way the goal could be defined as 'correct behavior'.

In the study of Devin and Alami (2016), ToM is used robot's adaptation of the changes during joint task with human. In the situation where the human missed the

instructions, robot either informs user or does the action per human. In this way, robot is reduced the unnecessary communication to produce less intrusive interaction with human, in other words, instead of repeating the information that human do not need, it gives the needed information to ensure successful task achievement. Also, human's cognitive load is not increased because of unnecessary information.

The work of Fiore et al. (2015) offers a system that has semi-observability. The belief notion of user is using to update their system and hierarchical Mixed Observability Markov Decision Processes (MOMPDs) planners for decision making.

### Belief-Desire-Intention (BDI)

In order to generate proactive behavior, the robot requires some knowledge of the human's mental state. We previously described ToM, a cognitive model concerned with understanding the human's mental state. Here, we introduce the Belief-Desire-Intention (BDI) model (Rao, Georgeff, et al., 1995), a computational model that proposes a formalization for the robot to estimate the human's mental state. It does so by reasoning about the human's *intentions*. This reasoning provides a link between the actions a human takes in the environment, and inferring their corresponding mental state.

Thus the BDI model provides an explicit, declarative reasoning on agent's<sup>2</sup> mental structures;

- **Belief** represents the beliefs about the environment, thus reflecting the knowledge/information state of the agent. Here, belief represents what the human knows about the environment.
- **Desire** represents the motivational state of the agent, or the desires that the agent has to bring about a certain *goal*. Here, the desire represents the human's desire to accomplish a certain goal (for example, the desire to find the nearest coffee shop).
- **Intentions** represent the deliberated state of the agent, i.e the what that the agent has committed to/*chosen to do*. Intentions can be thought of goals the agent has committed to some extent (such as starting the car in the desire to drive to the nearest coffee shop). This implies the execution of a *plan* to achieve the goal.

Beliefs may not represent ground truth of the environment (for example, a human may believe that the coffee shop they wanted to go is open, when it may have closed down a few weeks ago). It is therefore difficult for the robot to infer beliefs (particularly as they are represented in ToM) of the human, or what the human's knowledge is. Similarly, we may or may not know the desire of the human, as it may not be explicitly shared with the robot.

**Intention Recognition** In this thesis, we thus focus on the estimation of the human's intentions. As stated, intentions represent the path that the human takes to reach the goal. This path is manifested through actions taken in the environment. This is why, according to Bratman (1989), intentions are used link the human's actions with a human's mental state (under the assumption that actions are undertaken in

<sup>2</sup>Recall, that an agent represents an individual capable of performing an action, which could be the human or the robot. In this thesis, since we reason about the human's mental state, we henceforth use the term human to explain this model.



an environment having a particular intention). Thus we focus on estimating the intention, which is the underlying motivation of the human to achieve their goal.

To formalize, intentions are a mental state that a robot can infer through goal-directed actions. When we say goal-directed, this means a linear sequence of actions undertaken in order to work towards the achievement of a goal. Han and Pereira (2013) for example, defines intention recognition as inferring an agent's (humans) intention through analyzing its actions, and the resulting effects on the environment. According to Van-Horenbeke and Peer (2021), the term intent/intention recognition is discouraged due the lack of clear definitions across fields. For example, in natural language understanding, intent recognition is a task used to infer an intent from an input utterance of words (example, "Book me a train ticket to Paris" can have the intent to book train tickets). Whereas as the task is understood in robotics, it includes inferring a *final objective of the agent* (human), based on their current intentions.

Van-Horenbeke and Peer (2021) proposed to classify intention recognition systems into logic-based, machine learning based (i.e. probabilistic/classical and deep learning models) and brain-inspired approaches. In this thesis, we consider two classes of intention recognition approaches: logic based and probabilistic approaches.

**Logic-based approaches** are defined by a set of domain-independent rules that capture relevant knowledge to infer the human's intention through deduction (Sukthankar et al., 2014). The knowledge could be represented in different ways. In Planning systems, languages like the *Stanford Research Institute Problem Solver* (STRIPS) and *Planning Domain Description Language* (PDDL) describe the the environment's state and the effects of the possible actions. They use the descriptions for reasoning in order to generate plans to infer the human's intentions.

The logic-based approaches work well in highly structured environments, where there may be clear descriptions about the environment. Logic representation can define different kinds of relationships among entities, such as *types* (example coffee is a type of hot beverage). Those relationships can then allow the robot to recognize humans' intentions in the environment. Logic based approaches can be highly advantageous as they are very explicit. Using these logic representations, the system architect can easily understand steps taken in order to estimate the output. However, due to the explicit set of rules, logic-based systems cannot handle uncertainty, i.e new entities/relationships in the environment (Van-Horenbeke and Peer, 2021). Similarly, many logic-based approaches make the assumption that the human is rational, and thus acting in an optimal way, when it is often not the case (Dreyfus, 2007). Thus, logic-based approaches on real world problems are not generalisable. Thus, according to Van-Horenbeke and Peer (2021), a hybrid approach logic-based approaches with probabilistic reasoning techniques can overcome some of this uncertainty.

**Probabilistic approaches** Probabilistic approaches use probabilistic methods such as Bayesian networks and Markov models. Bayesian networks are generative probabilistic graphical models, where random variables are represented in a graph as vertices, and the conditional dependencies are represented as the edges connecting them. They can provide the probability distribution of any set of random variables given another set of observed variables. In this case, random variables could represent for example, the final goal, given the set of observed variables, for example, the goal-directed actions.

Though probabilistic approaches are good at handling uncertainty, as discussed in the logic based approaches, they have less interpretability in terms of understanding the reasoning leading to the output. Thus it is desirable to use a hybrid system of

both. Sometimes logic based systems use Bayesian inference to reason about intention. Such approaches are referred to as *Bayesian inverse planning*. Ramírez and Geffner (2009) propose an approximate planning method that generates a set of *possible* goals by using Bayesian inverse planning. Another example of a logic based approach strengthened with Bayesian inference is Persiani (2020). The authors use a logic based approach to generate an action plan for each goal, then use Bayesian prior function to infer human intention. In the thesis, we utilize a logic-based approach with Bayesian inference (probabilistic approach) as in Persiani (2020) to recognize intentions.

## 2.4 Conclusion

There are lots of different approaches studied in different domains in scenarios to generate proactive behavior almost in the past two decades. In summary, it is determined that proactive behaviors and especially the acceptance of proactive behaviors not only related with the quality of the generated behavior but also related with the task difficulties, certain user characteristic, personal traits, domain experience, interaction level (Kraus et al., 2020).

In this thesis, definition of proactive behavior based on Grant and Ashford (2008). Proactive behaviors are the autonomous behavior that robot self-initiate an action to assist the human for preventing the outcomes that the human may or may not know depending on the situation, in other words, being pro-social on the task level to help human on achievement of their task.

## Chapter 3

# Educational Task

*' The assurance of the future is based on education that has solid foundations, and education is based on teachers. '*

Mustafa Kemal ATATURK

In this chapter we present one of the application area of proactive robots. Educational applications open new rich and novel areas for HRI. This chapter, we will present why do we need proactive robots in education, an educational learning task (MobiAxis), the result of pilot study, and the outcomes for proactivity. MobiAxis, learning task was published in the workshop of Robots for Learning (R4L) at Ro-Man 2020. The learning task was developed within the ANIMATAS consortium in collaboration with other ESRs. The ESRs who collaborated on learning task other than the author (ESR 13 - Sera Buyukgoz from SoftBank Robotics, France) are ESR 4 - Karen Tatarian from SoftBank Robotics, France, ESR 8 - Sebastian Walkotter from Uppsala Univeristy, Sweden and ESR 1 - Rebecca Stower from Jacobs University, Germany.

### 3.1 Why do we need proactive robots in Education?

Education is one of the popular domain of HRI. Social robots can adopt the role of tutor or pair in education (Belpaeme et al., 2018). In the review of Belpaeme et al. (2018), the cognitive and affective outcomes of robot usage is showed alongside with highlighting importance of robot's behavior. The robot behavior is showed potential with the benefits of learning should support the various aspects of learning, personalized social support, display pro-social behaviors such as attention-guiding, displaying congruent gaze behavior, nonverbal immediacy, showing empathy. The review is directing the valuable research areas as engagement, persuasion, and compliance of social robots. In this section, we adapt proactive robot behavior in educational domain to benefit learners not specifically in engagement or persuasion but in general of cognitive outcomes.

The classroom are changing with the improvement of technology. It becomes more technology friendly with the usage of smart boards, robots, tablets. This is not the only change, those changes are affecting the learners profile. The educators stated that education style is changed over the time. Educationist Steve Ingle mentioned that in the past, teachers have been in control of learning process. Students come to a class and teachers start and in synchronous way, they take them through from A to B and then C. Lately, students are active in their learning, not just passive and contribute in interactive way. Students are interacting in asynchronous way with help of the technology. Students are in charge of decision according to at their own time and own pace, What do I need to learn right now? Do I need to learn A or Should I move to B?. This creates an interesting opportunities while creating new challenges



since the teachers are not in control once they were (Ingle and Duckworth, 2013). The proactive education is showing the great interest on supporting learner on different aspects.

Proactive teaching defined as a style of education that the teacher not only reacting when something occur but also anticipates what and when something happen and control the situation by empowering the learner (Denti, 2012). The empowerment is giving learner to autonomy and self-determination, confidence and capability. The example of proactive behavior of teacher to empower is defined by recognition and encouragement in Denti (2012). Recognition could be defined with positive feedback of an achievement such as 'good job', 'you did well'. While encouragement is most likely the constructive feedback such as 'you are doing well', 'keep going'.

As an overall summary, the classroom strategies are constantly evolving. Robots can benefit teachers on educational task if they can cope with the need of changing world. The current seems to be the proactive behaviors in education to cope with the cognitive level of education.

## 3.2 MobiAxis: A Learning Task

Social robots can offer many advantages over and above pure computer or tablet based learning activities, such as physical navigation of the environment, multi-modal social behaviors, and non-verbal communication (Fridin and Belokopytov, 2014; Leyzberg et al., 2012; Kennedy et al., 2015). However, many learning tasks which involve the use of social robots fail to take full advantage of the physical and navigational capacities of the robot. MobiAxis proposes a model which involves an educational learning task between a child and a robot. MobiAxis is designed around navigation, specifically targeting the concepts of number lines and multiplication of positive and negative numbers. This task was chosen as it allows for physical manipulation and navigation in space, maximizing the use of the robots physical capabilities. In addition, learning of mathematics has shown to benefit from the manipulation of tangible elements (Tsang et al., 2015). MobiAxis is also designed to investigate how specific socially intelligent behaviors can most benefit children's learning outcomes. In that case MobiAxis provides a chance to assess multiple dimensions of social robots, including proactive side of the robot.

The task of MobiAxis is comprised of four phases: *a demonstration phase* (where the robot performs an example of the task and the child observes), *a supervision phase* (robot acts as tutor whilst the child performs the task), *a teaching and learning phase* (child gives robot instructions) and *cooperation phase* (child and robot work together). Throughout these phases, the robot implements a number of multi-modal socially intelligent behaviors, such as; physical navigation of the environment, proactive engagement detection and adaptation, turn-taking, non-verbal communication through physical gestures, personalized feedback, adaption of different pedagogical roles (peer, tutor, novice).

One of the goals of MobiAxis is to explore how these behaviors influence children's learning outcomes. How these behaviors can be used to moderate social elements of the interaction such as trust, perceived agency, and engagement are also further research questions of interest.

### 3.2.1 MobiAxis Task Set-Up

MobiAxis is an educational task that requires a printed physical axis laid on the floor as a carpet, and an embodied robot. Both the robot and child navigate along the axis.

As such, the task maximizes use of the physical space to allow for better visualization and understanding of the concepts presented in each level. MobiAxis is aimed at teaching students between the ages of 10 and 12 the mathematical concepts related to multiplication of positive and negative numbers (i.e., how two negative numbers when multiplied together make a positive). The task is based around the commonly used format of number lines, but expanded to include orientation and navigation along an axis (promoting understanding of the concepts of direction and magnitude). Each level is made of three phases and a bonus phase (see *subsection 3.2.2*).

### 3.2.1.1 Key Mathematical Concepts in Learning Task

To demonstrate the multiplication of abstract numbers, It is important to define the key words: *orientation* and *direction* from blog of *Multiplying Negatives Makes A Positive 2021*. Orientation refers to the starting position of the navigator (robot or child). From zero, facing towards the positive axis constitutes a positive orientation, whereas facing towards the negative axis constitutes a negative orientation. The orientation is determined by the sign of the first number in the multiplication equation. The direction of movement along the axis can then be either forwards or backwards according to the current orientation. The direction of movement is determined by the sign of the second number in the multiplication equation. For example,  $+2 \times -3$ , the first number is  $+2$  implying the orientation is positive (facing towards the positive axis) and the second number is  $-3$  implying movement in the backwards direction along the axis. Note that if the example were reversed to be  $-2 \times +3$  the orientation would be negative and the direction forward, leading to the same final position.

### 3.2.1.2 Materials & Methods

MobiAxis is formed from two main material; axis and robot.

The axis used in MobiAxis is made up of red and blue bars, which alternate between odd and even numbers, respectively. The robot's eyes also change color to coordinate with the bar (unit) it stops on. This allows the child to detect accurately where the robot has stopped. In addition, the axis has intervals of step units of 26 cm and the axis goes from  $-10$  to  $+10$ . Figure 3.1 shows a shorter version of the axis going from  $-5$  to  $+5$ .

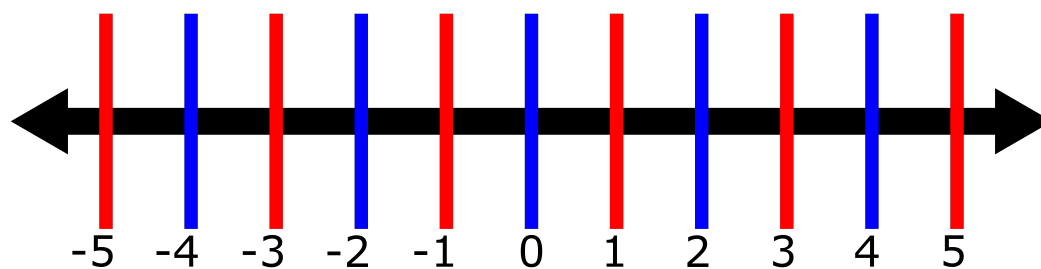


FIGURE 3.1: A shorter version of the axis used in the Learning Task, MobiAxis

The robot used for MobiAxis is Pepper Humanoid Robot<sup>1</sup>. The robot has three main poses, which are shown in Figure 3.2. At the beginning of the task, it is located at *pose 1*, where it is positioned at the zero position of the axis, facing the child, with both of its arms lifted 90 degrees. First, the orientation of the robot is chosen by touching

<sup>1</sup>Pepper robot by SoftBank Robotics [www.softbankrobotics.com/emea/en/pepper](http://www.softbankrobotics.com/emea/en/pepper)

the hand of the side that the robot needs to face (right hand for positive orientation, left hand for negative orientation). This causes the robot to move to *pose2*, where it is still at the zero position of the axis and facing the child but this time only the chosen arm for orientation is raised. Second, the number of times the selected hand is tapped specifies the step size, where  $stepsize = numberoftaps \times [fixedstepunit]$  with the step unit being prior set and constant throughout all levels. Third, the direction is selected on the tablet of the robot. At this point, the robot switches to *pose3*, where it is still at the zero position but facing the chosen orientation, having both arms down. Finally, the number of steps, which is how many times the step (which has the length of the registered step size) is repeated, is registered by the number of times the robot's head is tapped. In Figure 3.2, the *pose 2* shows the right hand raised indicates that the positive orientation was selected while *pose 3* has the robot turned facing the positive side showing that the robot has oriented positively. Note, in *pose 3* of Figure 3.2 only shows orientation, if the direction was selected to be positive then the robot would move forward on the axis and if selected negative it would move backwards on the axis.

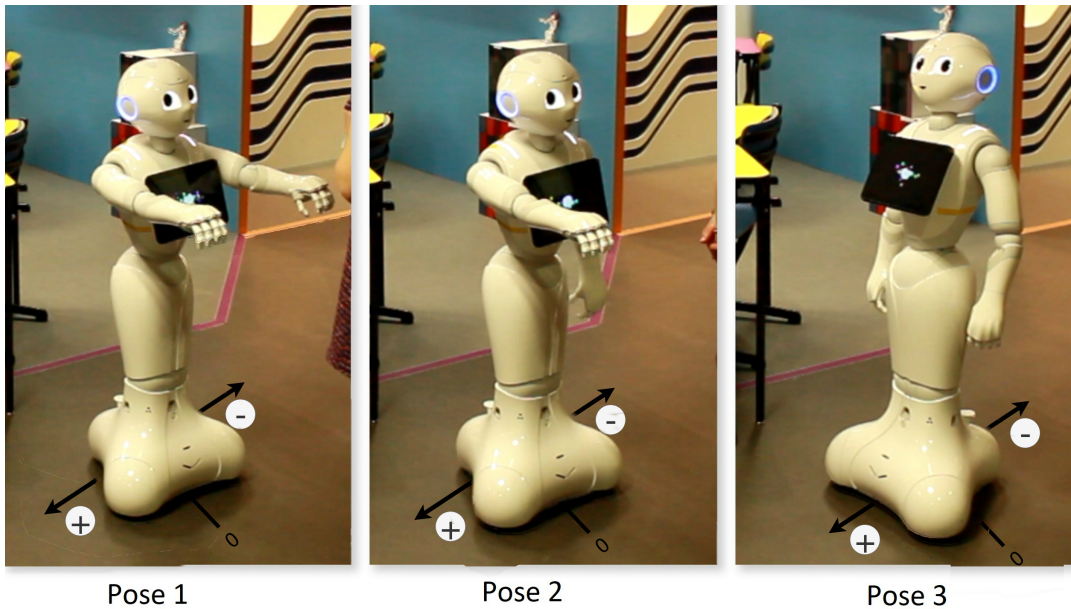


FIGURE 3.2: The three poses of the Robot for selecting orientation & direction. Pose 1 is position of the robot for selection of the orientation. Pose 2 is position of the robot, when the orientation is selected and robot waiting to step size. Pose 3 is position of the robot, the robot pursued the orientation and waiting for the selection of the direction.

### 3.2.1.3 Implementation on the Pepper robot

The Pepper robot runs on the operating system NAOqi, defined by Pandey and Gelin, 2018. NAOqi has an application programming interface (API), which is a set of different modules for controlling and accessing the robot, and creating applications. In our application, the NAOqi APIs<sup>2</sup> are used for low-level robot control and perception. The Python software development kit (SDK) of NAOqi is used for the programming task itself. In this implementation, we used version 2.5 of NAOqi and version 1.8 of the Pepper robot. One major improvement in this version, compared to the previous

<sup>2</sup>NAOqi Documentation <http://doc.aldebaran.com/2-5/naoqi/index.html>

versions, is an updated localization framework. It improves dead reckoning for both, transnational and rotational movements, providing good enough out of the box accuracy for navigation in MobiAxis.

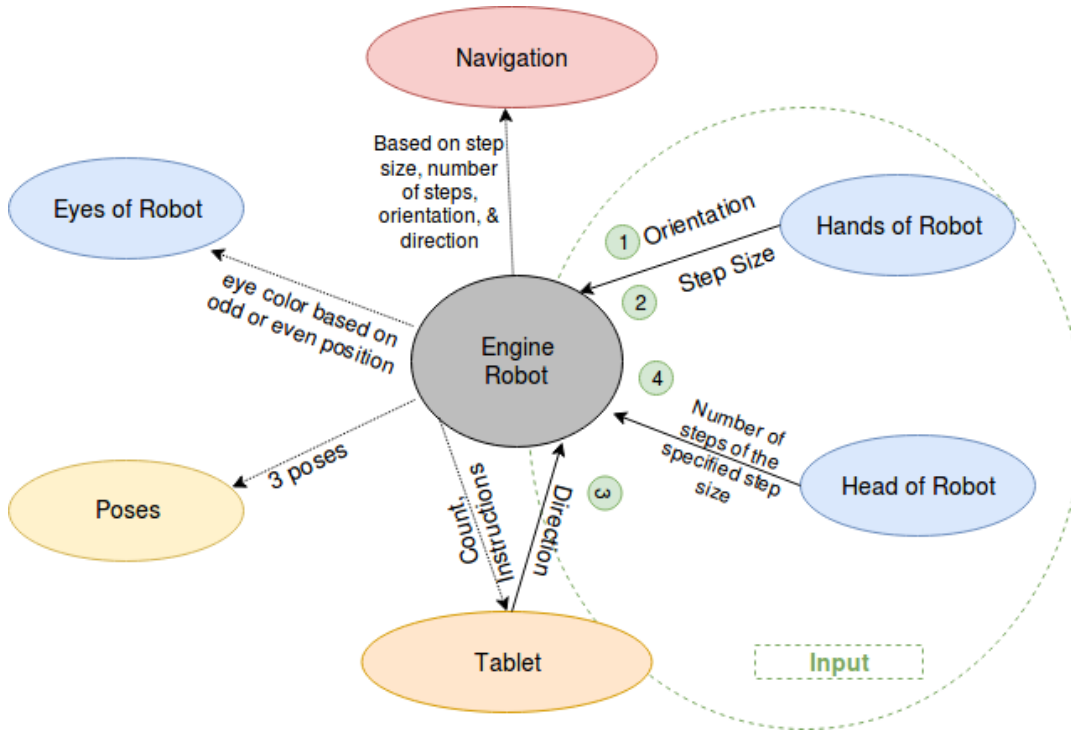


FIGURE 3.3: Model of Implementation is emphasized multi-model features of interaction. Input interactions (touching hands, head and tablet) and output reflection on robot.

As shown in Figure 3.3, we have four different types of inputs, which are received from different services of NAOqi APIs. Touch sensors, which are placed in the hands and head of robot, are accessed through the 'ALSensors' services. Through that service, the listener of each sensor is raised when its respective sensor is touched. During the task, we only subscribe to the sensors when it is necessary. For example, after the desired hand of the robot has been selected, we unsubscribe from the sensor of the arm that was not chosen, and instead, the script moves into the counting loop for calculating the step size based on the sensed taps on the chosen arm. Meanwhile, the tablet is displaying the registered choices made by the user. After this step, the user is asked to select the direction on the tablet. 'ALTabletService' services are used to display a certain output on the tablet, in addition to receiving input from it. On the other hand, the 'ALMotion' service is used to control the movement of the robot. It is used to control the robot's transition from one pose to another, its orientation, and its navigation in the selected direction. The animations of poses are defined as a result of angle interpolation done by setting the position of each key frame and the time interval in which the action appears. Figure 3.2 shows the poses and the transition between them. Furthermore, to match the reached destination on the axis on which the robot is navigating 'ALLeds' service is used to specify the eye color, which is either red if the number reached is odd or blue if it is even. Finally, 'ALTextToSpeech' service is utilized to create the speech of the robot while Pepper is giving the instructions, counting the step size, and asking for verification from the user. Figure 3.4 shows how task iterates each actions by employing the services described above.



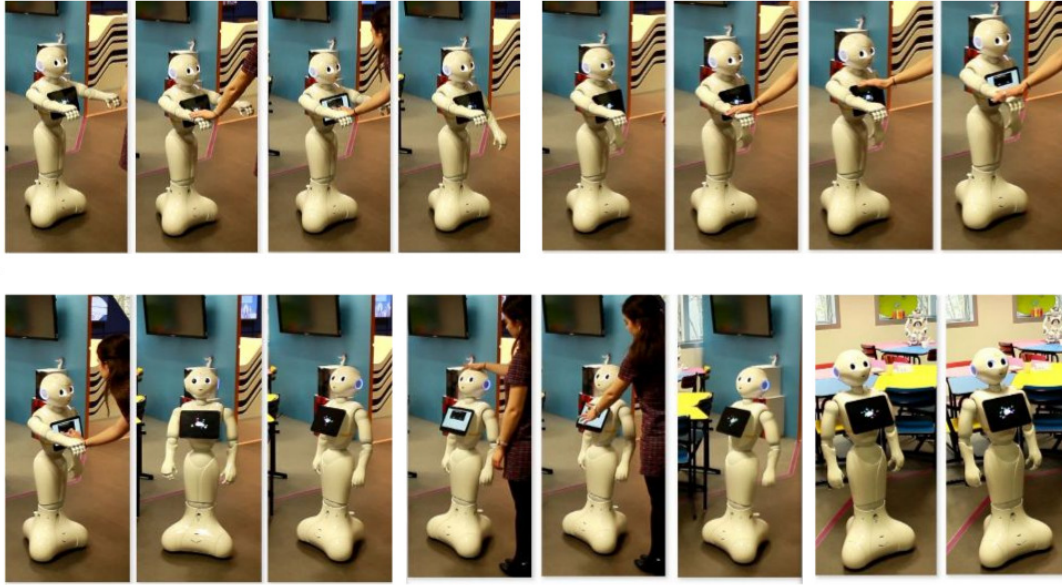


FIGURE 3.4: Time-line for instructing the robot to complete the mathematical equation. It starts with robot asking the equation and ended with new position of the robot on the axis.

TABLE 3.1: Summary of Phases in Each Level of MobiAxis

Phase	Role of Robot	Description	HRI Interest
<i>Phase 1:</i> Demonstration	Demonstrator	Robot shows child an example by performing it	Basis of trust model, & role of robot
<i>Phase 2:</i> Supervision	Tutor	Robot supervises the child as they complete an exercise on the axis as described in subsection ??	Demonstration of turn-taking, basis for trust model, & role of robot
<i>Phase 3:</i> Teaching & Learning	Peer	Child instructs the robot on how to move while robot gives feedback	Model of trust, theory of mind, how the robot learns from human input, learning by teaching, feedback system, role of robot & displaying multi-modality of social intelligence
<i>Phase 4:</i> (Bonus Phase) Collaboration	Peer Collaborator	Child and robot both work together towards solving a problem	Model of trust, displaying multi-modality of social intelligence, role of robot, degree of collaboration, displaying turn-taking, & proactivity

### 3.2.2 Phases of the Learning Task

MobiAxis is comprised of several mathematical lessons related to multiplication, direction, and orientation. Each lesson is covered in one level. For instance, *level 1* covers multiplying positive numbers, while *level 2* and *level 3* go over multiplying positive and negative numbers and multiplying arbitrary numbers, respectively. Each level is made up of 3 phases, plus a bonus phase. In each phase, the robot plays a different pedagogical role to explore additional HRI research questions. The phases are summarized in Table 3.1. Between each phase, the robot and the child interact to discuss the task.

The phases of each level are designed to increase the learning gains from the activity and inspired by the building blocks presented in a blog article by Concordia University-Portland. The teaching strategies for teaching mathematics include repetition, time testing, pair work, and manipulation tools.

First, repeating and reviewing previous formulate to help facilitate learning and memorizing (C. Toppino and Gerbier, 2014). As such, MobiAxis repeats the same lesson in the several phases, but in each phase with some variation. Second, time testing of the material is used to keep track of the student's progress. In MobiAxis, time testing takes place in the interactions between the robot and student in between the phases. Third, students can ameliorate their critical thinking and problem solving skills, in addition to expressing themselves by group work in mathematics (Fidan Koçak et al., 2009). For this reason, MobiAxis includes pair work between robot and child through the last two phases of each level. Finally, the manipulation tools used to teach mathematics are implemented through the navigation on the axis and the use of tablet on the robot.

The first phase is *Demonstration*, where the child learns by observing, followed by the second phase *Supervision*, where the aim is for the student to learn by doing the task alone for the first time and receiving feedback from robot about their decisions. This is then followed by the third phase *Teaching & Learning*, where the student is able to learn by teaching the robot, and finally for advanced lessons there is a fourth phase *Collaboration*, where the students collaborates with the robot to solve a problem. The sequence of the phases is chosen so that the child can experience several learning strategies and we can track the learning gains throughout.

#### 3.2.2.1 Phase 1: Demonstration

This is the first phase of a level where the robot demonstrates to the child what is orientation, step size, step numbers, and direction by performing an example. For instance, a possible scenario would be the one shown in table 3.2. The purpose of the first phase is to have the child learn by observing before attempting to do it himself. It is the first part of the interaction between the child and the robot, and as such forms a basis for the trust model between them. In addition, the child is exposed to the first role of the robot as a demonstrator.

#### 3.2.2.2 Phase 2: Supervision

In the second phase, the robot becomes an observer and the child performs the task alone by navigating along the axis. The child has to physically perform the orientation and direction and walking on the axis. The robot gives feedback to the child based on the performance and the decision he/she makes. Moreover, it proactively corrects the child's decision. For example, the robot can warn the child if he/she is looking in the wrong direction and and/or calculating incorrectly. This phase allows us to explore

TABLE 3.2: Phase 1: Demonstration, an example scenario

**Pepper:** “To calculate  $-2 \times 3$ , I first need to work out which way I should turn, and the size of my steps. The first number is negative 2, which means I need to face the negative axis. This also means my step size is 2 units”.

*Pepper turns 90 degrees*

**Pepper:** “Now I need to calculate my direction and the number of steps I should take. The second number is positive three, so I need to move forward. So now I need to repeat the step size of 2 units 3 times”.

*Pepper moves to -6*

**Pepper:** “When I multiply  $-2 \times 3$ , I get  $-6$ .”

the child’s theory of mind regarding the robot and the trust model in the interaction. Furthermore, the feedback system allows us to test the right and wrong modalities and explore how accepting the child is of the suggestions and the comments made by the robot. The phase ends when the child completes the exercise. This forces a turn-taking interaction between the child and robot. Additionally, the pedagogical role of the robot changes to tutor.

### 3.2.2.3 Phase 3: Teaching & Learning

In the third phase, the robot listens to the child for instructions on how to complete the exercise. The robot navigates along the axis whilst the child gives instructions. Table 3.3 shows an example of scenario for Phase 3. In this phase, we can test the effect of the robot’s proactivity on the child’s engagement in the game. When the child loses focus, the robot can remind him or her to continue with the task. Finally, we can also study the way the robot learns from the human input. In a sense, the child is also teaching the robot how to solve the problem.

TABLE 3.3: Phase 3: Teaching &amp; Learning, an example scenario

**Pepper:** “Wow! You seem to have mastered this! Can you help me to calculate  $-2 \times 3$ ? First, tap one of my hands to tell me what side I should face.”

**Child:** *taps left hand*

**Pepper:** “That is great! Please tap on my hand again to tell me how many units the size of my steps should be”.

**Child:** *Taps left hand twice* *Pepper turns to face negative axis*

**Pepper:** “Which direction should I go now? Use my tablet to tell me forward or backward”.

**Child:** *Taps ‘forward’ on the tablet*

**Pepper:** “Tap my head to tell me how many times you would like me to repeat the unit step size of 2”

**Child:** *Taps head 3 times*

**Pepper:** *moves forward along the negative axis to -6.*

### 3.2.2.4 Phase 4: Collaboration

The fourth phase only exists for advanced levels. In this phase, the robot acts as a collaborator and the child and robot have to perform the task together to achieve the final answer. For example, the child can be the one who chooses the orientation, but

it would the robot choosing the direction. In the future, the axis can also be used to learn how to add vectors and as such the child can be one vector and the robot another and they have to collaborate to find the answer.

### 3.2.3 Evaluation of Learning Task

The learning task involves 3 main metrics by which to evaluate the effectiveness of the robots social behaviours; learning, engagement, and trust.

#### 3.2.3.1 Learning

Learning in this context refers to the learning gain in the specific topic of interest being taught (in this case, multiplication of positive and negative numbers). Children will be administered a pre-test and post-test before and after interacting with the robot to assess their knowledge of multiplication. The scores on these tests can then be compared in order to detect if there is any improvement. Additionally, throughout the interaction, other metrics such as number of errors made by the child, time taken to complete an exercise, and advancement through the phases can be used to assess learning.

#### 3.2.3.2 Engagement

Engagement can broadly be defined as the establishment and maintenance of connections between two (or more) agents involved in an interaction (Sidner et al., 2005). In review of Oertel et al. (2020), this definition referred as a social engagement and mentioned engagement could be treated as state (engaged - not engaged) and process continues through interaction. Engagement can further be broken down into two sub components; *task engagement*, which refers to engagement in solving a problem, and *social engagement*, which refers more to the social relationship being formed between participants (Corrigan et al., 2013). In human-human studies, detection of social relationships shows the negligence or controlling behavior of agent (Leclere et al., 2016). Moreover, Oertel et al. (2020) proposes education domain is interesting domain for task vs social engagement, also it will create necessity to focus on the conceptualization of task engagement and how social and task engagement are related to one another in a longer-duration interactions. *MobiAxis* will include elements of both social and task engagement. Having those two components named as Productive Engagement by Nasir et al. (2021) which is stand for engagement type which optimizes the learning gain. Both objective and subjective (self-report) measures can be used, including, but not limited to, checking for length and frequency of eye contact with the robot, and self-report questionnaires. For example, camera's could be used to detect frequency and length of eye contact with the robot versus with the task (Anzalone et al., 2015). In addition, after completing the interaction children will be asked to respond to some questions regarding their interaction with Pepper.

#### 3.2.3.3 Trust

Similarly to engagement, trust can be broken down into two components; social and competency (Gaudiello et al., 2016; Straten et al., 2018). Social trust refers to more affective based trust with regards to the social relationship formed with the robot, whereas competency trust is an evaluation of the robots perceived capabilities. Competency based trust can be evaluated through willingness to adhere to the robots



suggestions (Stower, 2019). Social trust can be measured through self-report measures such as desire to be friends with the robot, or objective measures such as amount of information disclosed to the robot throughout the interaction (Stower, 2019).

### 3.2.4 Discussion

Pepper, in the current application, navigates and acts as a peer for the student, as well as a collaborator and teacher, switching roles depending on the situation, as suggested in Section *Phases of the Learning Task*. However, the robot can have further social features that can improve the interaction between it and the child. In the further stage of the educational task, it is aimed to add socially intelligent characteristics to better explore HRI research questions related to engagement, trust, and learning. First, it is believed that designing an engagement detection model could improve the interaction that takes place in between each phase. This is used to help the robot be more proactive. For instance, if engagement is detected to be too low, the robot can act proactively to increase it or ask for teachers help. Thus, it is important for the robot to know the user's needs and adapt to them. In addition, it is important for the robot to exhibit turn-taking mechanisms to be able to play the role of a peer and collaborator. Multi-modal, socially intelligent behaviors are also necessary in order to be perceived as an intelligent agent. In addition, we would like to gamifying system by adding a proactive feedback and point collection system. The robot would give proactive feedback to the student specifically in the second and fourth phases to help guide him/her to the right answer while letting him/her learn and explore. The proactive feedback system would also adapt to the child's progress. The robot would reward the child with points for getting the right answer and improving learning gains.

The reason behind including such features and models is to be able to better explore how socially intelligent behaviors influence children's learning outcomes. Firstly, multi-modal social behaviors and their perception as a unified construct are highly important in order to attain desirable outcomes with social robots and better learning data (Kennedy et al., 2017). In addition, the findings in (Kennedy et al., 2017) suggest that there is a strong positive correlation between ratings of tutor nonverbal immediacy and performance in a one-on-one maths tutoring task between robot and student. However, the exact effects that the verbal and non-verbal behaviors, such as emotional expression and multi-modal, socially intelligent behaviors (*e.g.*, joint attention, gaze mechanisms, and gestures), have on children's interactions with social robots is still unclear, especially for children's trust in robots and the benefits for learning (Stower, 2019). Secondly, proactive behavior is intended to not only take initiative when an action occurs but to also take initiative before an action happens by anticipating the needs of the user. The proactive model that we hope to implement would include anticipating user needs, improving the robot's knowledge such as validation results or asking missing points (Lemaignan et al., 2010), increasing engagement and interaction by proactively seeking users for interaction (Garrell et al., 2013), learning algorithms, and considering user's actions and feelings such as cooperative manipulation (Bussy et al., 2012; Thobbi et al., 2011) and the balance for the robot not to become annoying (Rivoire and Lim, 2016). We hypothesize that the proactive behavior of the robot would increase the engagement of the user. It has been shown that such proactive behavior may be vital to allow the robot to effectively engage users (Liu et al., 2018).

### 3.3 Pilot Study of MobiAxis

A pilot study is conducted during Science Festival of Sorbonne University, 2019. For this experiment, the focus was only the teaching and learning phase of the MobiAxis task. This was done due to both the time constraint of running the experiment in the wild, and to allow for investigation of the short-term setup before developing longer-term applications. In addition, we added the three feedback mechanisms to the task.

#### 3.3.1 Design

Feedback mechanism designed for answering empowering of proactive behavior while keeping the simplicity of the task and interaction. Three different mechanisms designed for comparing each other and researched which strategy has a high impact on children and best suitable for their needs. Those strategies are positive feedback, negative feedback and constructive feedback. There is also condition that robot is not giving any feedback. That condition created as a control group. Examples of the robot's verbal reactions to the different conditions are shown at the Table 3.4.

##### 3.3.1.1 Positive Feedback

In this feedback style, users only get praise. In the scenario, during selection of orientation, direction and setting the number of step process, if the user set the right selection or right number, robot praises to users each time by giving simple comments such as amazing and perfect. Those sentences are not related with overall result of the question. User still need to validate their answer after the selection process finished. They could ignore the feedback and continue with their choice.

##### 3.3.1.2 Negative Feedback

In this feedback style, users only get complains. Contrary to the positive feedback, when the user set a correct selection no feedback is given. However, if the user set a wrong selection the robot takes initiative and inform the user about the error even the user can not correct the selection. In the scenario, the robot inform the user if the selection is wrong. Only, if the user set more steps than the actual results, the robot take initiative and not only inform user but also repeat the set process. If user already validate the answer before setting the correct answer, then robot prefer to stay silent since the system already continued with next action.

##### 3.3.1.3 Constructive Feedback

In this feedback style, users always receive assistance. It consists of a combination of positive and negative feedback. In all cases the robot gives feedback to the user (for both correct and incorrect answers). Whilst the user is counting the robot encourages the user until the correct answer is reached, validated using positive feedback. If the user continues to add, the robot uses negative feedback and resets the answer to zero.

##### 3.3.1.4 No Feedback

This is the control group. In this condition the robot does not give any feedback, and does not interfere with the user's decision. Once the user is completed the question the robot only tell the answer is right or wrong.

TABLE 3.4: Examples of the robot's verbal reactions for the different conditions

Selection Process	Status of Answer	Positive Feedback	Negative Feedback	Constructive Feedback
Selecting Orientation	True	Amazing!	-	Amazing!
	False	-	Try again!	Try Again!
Set Magnitude of Step size	<	-	-	Keep Going!
	=	Perfect! You could validate the result	-	Perfect! You could validate the result
	>	-	Try again! <i>magnitude set to zero</i>	Try again! <i>magnitude set to zero</i>
Selecting Direction	True	Selection right!	-	selection right!
	False	-	Selection Wrong!	selection Wrong!
Set Magnitude of step	<	-	-	Keep Going!
	=	Perfect! You could validate the result	-	Perfect! You could validate the result
	>	-	Try again! <i>magnitude set to zero</i>	Try again! <i>magnitude set to zero</i>

Validation process is unrelated to the robot behavior, in any time of the interaction, the user choose to validate answer and continue with next step. In this way, users have a freedom to act according to their will. Validation process also gives chance to users reconsider their choice and it create space if users want to change their selection. Unless feedback is given an additional chance to perform well, it is not a good feedback (Brookhart, 2017).

### 3.3.2 Participants

22 child mainly were recruited the experiment during a Science festival (Fete de la science) at Sorbonne University, Paris in October 2019. Children were aged between 7 and 12 ( $M = 9.6$ ,  $STD = 1.72$ ). They were in class between primary school to middle school. Participants were randomly assigned either to the control group (i.e. no feedback) or one of the three condition groups (i.e. positive feedback, negative feedback or constructive feedback). In some conditions more than one participant participated at the same time. In each condition approximately 4 group participant participated, some group has more than one participants. Experiment conducted in French. System was explained to them by a french speaking experimenter. All interactions were guided by the same experimenter. During the recruitment process, gender of participants were not highlighted, age and the level of educations were considered.

### 3.3.3 Setup and Materials

This experiment was conducted by using Pepper Humanoid robot (SoftBank Robotics). The task was carried out in an open area of Sorbonne University. An axis with range from -5 to 5 was created by using adhesive tape. The robot was placed on an axis which is stuck to the ground as shown in Figure 3.5.

### 3.3.4 Questionnaire

After interacting with the robot, the user was asked to fill out a self-report questionnaire (16 questions) regarding their impressions of the robot. The questionnaire was divided into 5 sub-scales; social trust in the robot, perceived competency of the robot, social affiliation with the robot, perceived agency of the robot, and moral concern



FIGURE 3.5: Visualization of the experimental setup

for the robot. Example questions for each sub-scale can be seen in Table 3.5, which is adapted from Stower, 2019. All questions were posed using a 5 point Likert scale ranging from 1 (a big no) to 5 (a big yes). This scale was chosen for its simplicity and appropriateness for multiple age groups. All children answered all questions in the same order. Questionnaire also includes the age and level of education of the user as well as the mathematical questions that they solved together with the robot.

### 3.3.5 Procedure

The examiner welcomes the participants. Examiner explains how the task work to each new participant. After the demonstration finish, examiner step back and let the user approach to the robot. Then, teaching and learning phase start. During the teaching and learning phase, the robot gives three different multiplication problems. Same problems are given to the same order to each participant, which are respectively;  $(2 \times 1)$ ,  $(2x - 2)$ , and  $(-1 \times 3)$ .

### 3.3.6 Results

For the overall evaluation score of the questionnaire, shown in Figure 3.6, a between subject study conducted and verified with Analysis of variance (ANOVA) statistical test. No significant main effect was found ( $p = 0.096$ ) when looking

TABLE 3.5: Post-Assessment Questionnaire of Experiment

Sub-Section	Statemets in English	Statemets in French
Social Trust	Pepper keeps my secrets Pepper is honest I trust pepper	Pepper peut garder l'un de mes secrets Pepper est honnête J'ai confiance en Pepper
Competancy Trust	Pepper has a lot of knowledge Pepper is smart Pepper is reliable Pepper is a good teacher	Pepper a beaucoup de connaissance Pepper est intelligent Pepper est fiable Pepper est un bon enseignant
Social Affiliation	Do you like Pepper? Does Pepper like you? Could Pepper be your friend? If you were sad, would you like Pepper to comfort you?	Aimes-tu Pepper? Est-ce que Pepper t'aime? Est-ce que Pepper pourrais etre ton ami? Si tu étais triste, aimerais-tu que Pepper te réconforte ?
Agency / Mind Perception	Can Pepper be sad or happy? Does Pepper think? Can Pepper move around on its own? Can we turn Pepper off or on?	Est-ce que Pepper peut être triste ou heureux ? Est-ce que Pepper pense ? Est-ce que Pepper peut se deplacer tout seul ? Est-ce que l'on peut éteindre ou allumer Pepper ?
Moral Concern	Is it bad to hit Pepper?	Est-ce grave de taper Pepper ?

over all constructs and independent variables. However, significant effects were found in comparing constructs of Competency Trust with Agency/Mind Perception ( $p = 0.019$ ) and Social Affiliation with Agency/Mind Perception ( $p = 0.041$ ).

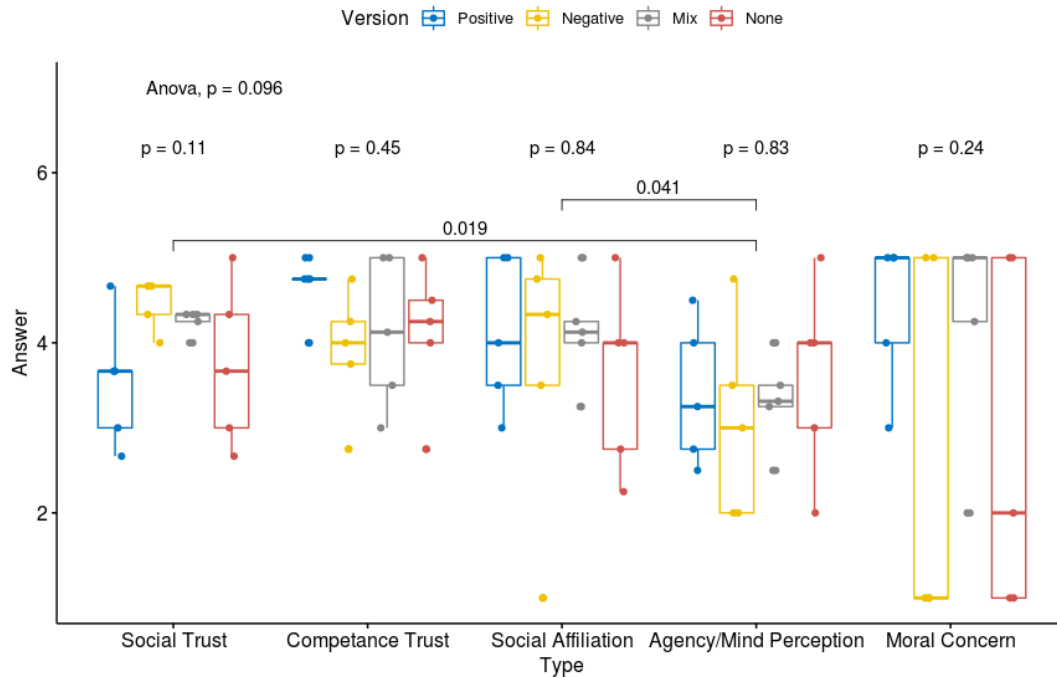


FIGURE 3.6: Overall evaluation of the questionnaire

Moreover, significant results can be seen when taking a closer look. For instance, conducting a repeated measures ANOVA to compare the positive feedback variable and the negative feedback variable, seen in Figure 3.7, highlighted a significant effect in the social trust construct ( $p=0.035$ ) despite the lack of significant results for the overall evaluation ( $p=0.3$ ). In addition, the positive feedback scored less than the negative feedback in the social trust but scored higher in the competency trust.

In addition, comparing negative feedback to no feedback has shown that there is no significant effect ( $p=0.11$ ) as shown in Figure 3.8. While the negative feedback scored higher in the social trust, for the remaining constructs there was relatively no significant or seen difference.

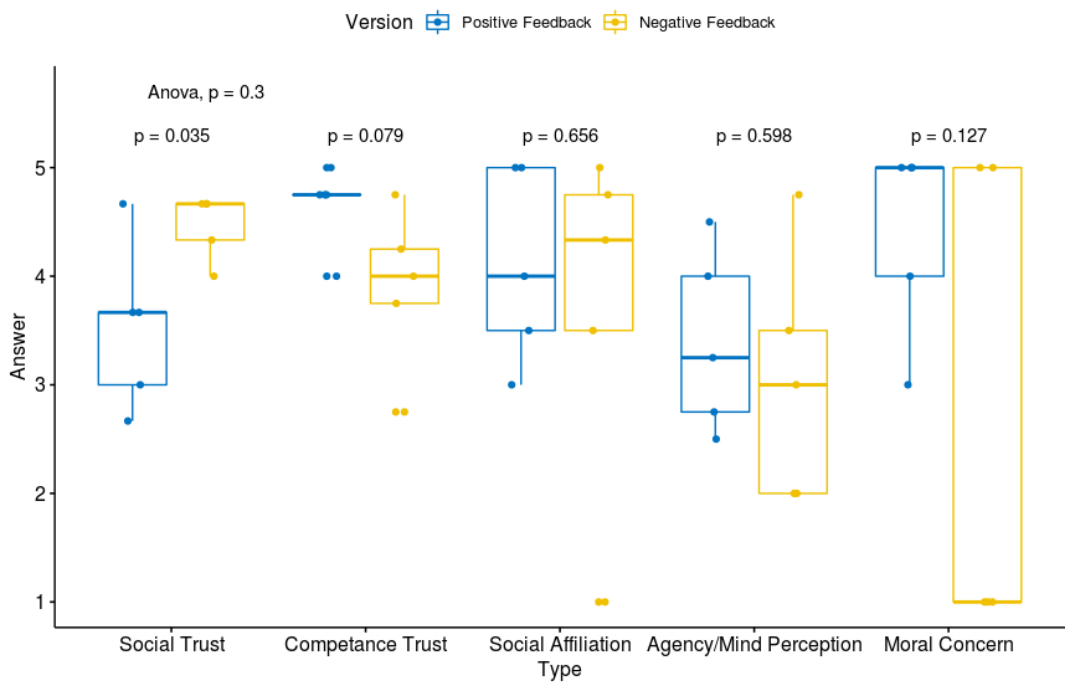


FIGURE 3.7: ANOVA Comparison of Positive and Negative feedback

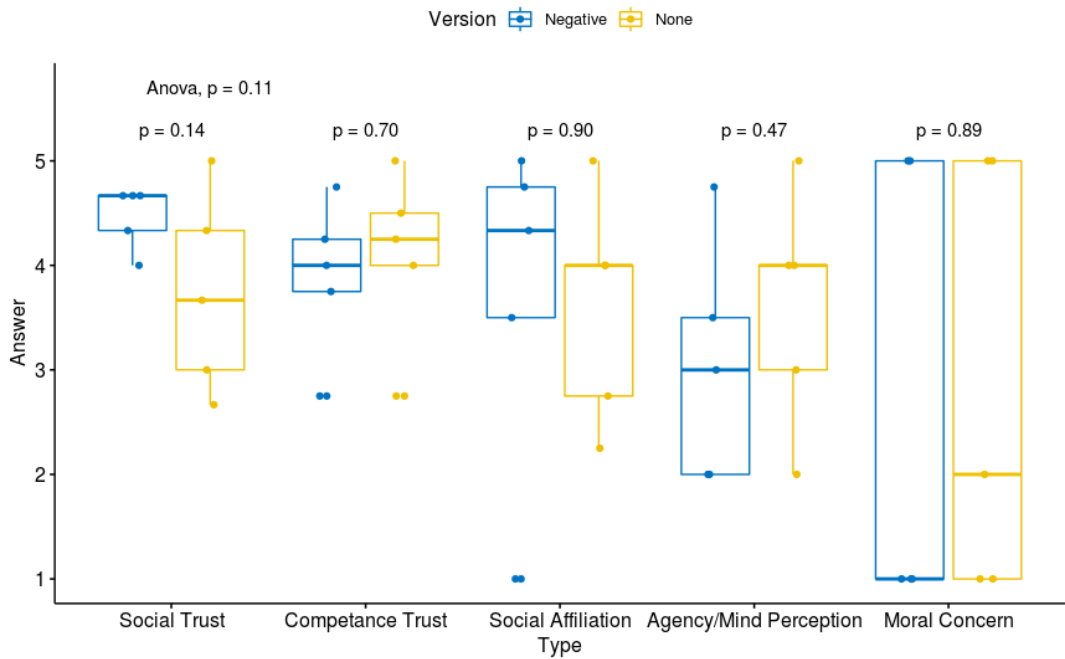


FIGURE 3.8: ANOVA Comparison of Negative Feedback and No Feedback



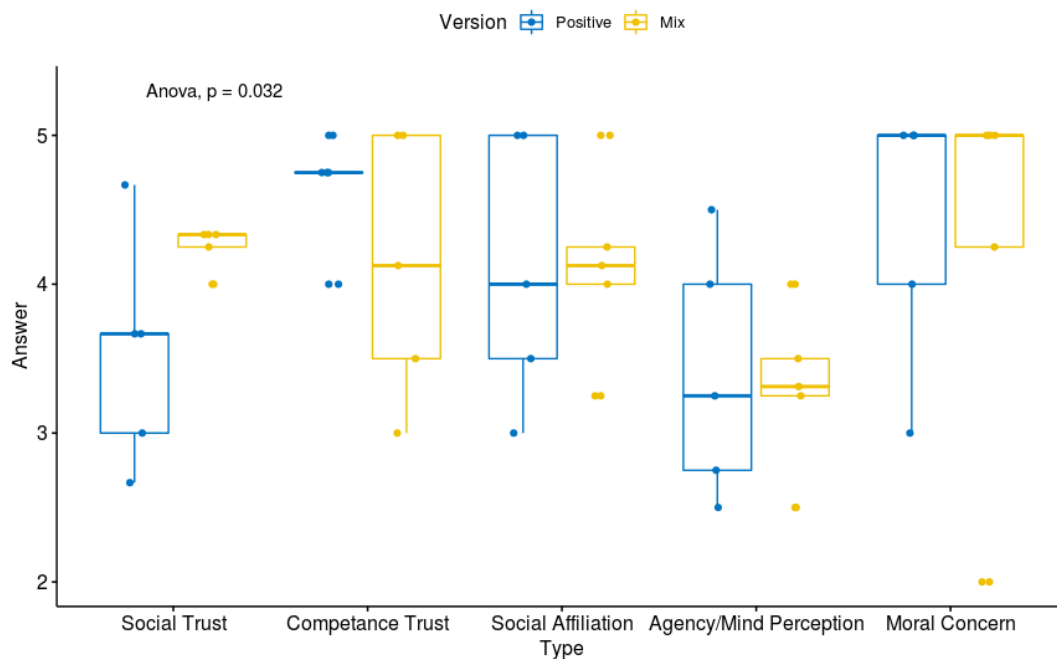


FIGURE 3.9: ANOVA Comparison of Positive Feedback and Constructive Feedback

Furthermore, a significant result is found when comparing positive feedback and mix feedback, which is composed of both positive and negative feedback. Mix feedback scored higher in the social trust than the positive feedback. This is displayed in Figure 3.9.

### 3.3.7 Discussion

In this study, proactive behavior of the robot presented in different feedback forms (positive, negative and constructive) for empowering the user. We can not conclude a significant result from small and sparse sample data, as it is shown in the results. Thus, this study gives many hindsight towards the need of user and the adaptation of robot behavior.

In general most of participants were enjoyed because they were playing with the robot. It was already fascinating for them, regardless of the robot's behavior. They did not pay attention to robot's speech or behavior. Majority of participants were not letting robot to finish its speech. They act before the robot finish. Participants only faced with one version of experiment's conditions. Since they only faced with one condition and already not focused on the robot behavior, it created a lack of understanding about differences between conditions.

All interactions held by same experimenter. This means each participant got the same level of interruptions and instructions. However, during the experiment, participants were more attentive to what experimenter was saying than what robot was saying. At the first phase the experimenter demonstrated and explained how the task work. We believed it was the reason that experimenter did not leave the robot and participant alone after demonstration phase. Since the experimenter was still near to the robot, the participants tends to accept experimenter as an authority and seek validation from the experimenter before touching the robot.

The validation seeking behavior was an unexpected behavior of participants. It was believed that helping the participants during their decision is enough, however, participants were seeking validation before they initiated the interaction. During the majority of the interactions, in each step participants looked at the experimenter or other adults to seek validation for their answer before they validate themselves. As the nature of the experiment, robot was silent till participants initiated the interaction. That's why it is believed that the feedback interruption later was given by robot was mostly ignored. It was ignored in the level that for negative feedback behavior was not initiated at all from robot side.

During the experiment, we tried to assess the difference in mood of the participant according to following given feedback. This part was failed in regard of detecting the mood. We tried to utilize mood detection algorithm which is already part of Pepper robot's API. The environment set up was not suitable to detect mood of the participants. Most of the time, robot failed to detect the observed mood of the participant. It either tracking another person from the crowd instead of the participant or the participant not placed on the right angle or distance for the mood detection.

### 3.4 Conclusion

In this chapter, we discussed one of the application domain of proactive robot behavior; education. During the chapter, the importance of proactive robot behavior in classrooms is highlighted, which is a robot that could anticipates the need of the learner and could act beforehand the learner demand. MobiAxis, educational task, is presented. MobiAxis highlights the importance of the physical presence and learning abstract concepts of mathematics. In the pilot study of MobiAxis, learning gain could not able to verified but some hindsight about the hidden struggles of initiating proactive behavior is explained. Proactive behavior of the robot presented as a different form of feedback that aims to empower the user. The major struggle is handling the validation seeking of the user and the users tendency to not listening robot when there is another human at the environment. Those points used to define the generic architecture of proactive communicative robot behavior.





## **Part II**

# **Architecture**



## Chapter 4

# Architecture

*Deliberating on you is a beautiful, hopeful thing  
It's like listening to the most beautiful song  
From the world's most beautiful voice...  
However, hope isn't enough for me any longer  
I don't want to listen to songs no longer,  
I want to sing them*

Nazim Hikmet

This thesis focuses on making the robot proactive during interaction with humans. In this sense, the robot takes the initiative to assist. Proactive robot behavior is making a robot gain the ability to intervene. As well as proactive communicative robot behavior is the ability of the robot to reason of own knowledge and instantiate a communicative action directed to the human with the aim of playing a role to change of the future.

The definition highlights the importance of forecasting the future and understanding the human's state of mind. Forecasting the future helps to detect the problems that could occur because of our current actions. In the examples of emergency exits, if a person blocks the emergency exit, people who live in that building will suffer in case of fire. Therefore, not blocking the emergency exit of a building is common sense. However, to apply that common sense, the robot should have reason about the possible future effects of the current action.

In general terms, the proposed framework is shown in Figure 4.1. On a broader level, those components are **knowledge model** where all the information stored, **reasoning model** where all the reasoning about the knowledge happen, **proactive behavior model** where proactive behavior generation happens and other modules **perception model** where all the raw data sorted and structured from the environment and **executor model** that is converting proactive commands to robot actions.

It is aimed to create a generic framework that could initialize the proactive behavior. The main focus of this thesis is the proactive behavior model, which is responsible for the generation and instantiation of the proactive communicative robot behavior. It is already mentioned that without using other models, it is impossible to anticipate the need and initiate the proactive behavior, definitely not in a generic manner, as the remainder of the difference between proactive and reactive behavior. Proactive behavior is the one that can follow the demand or initiate action regarding the consequences of that action. The following sections explain how those modules are defined to be helpful to the generation of proactive behavior.

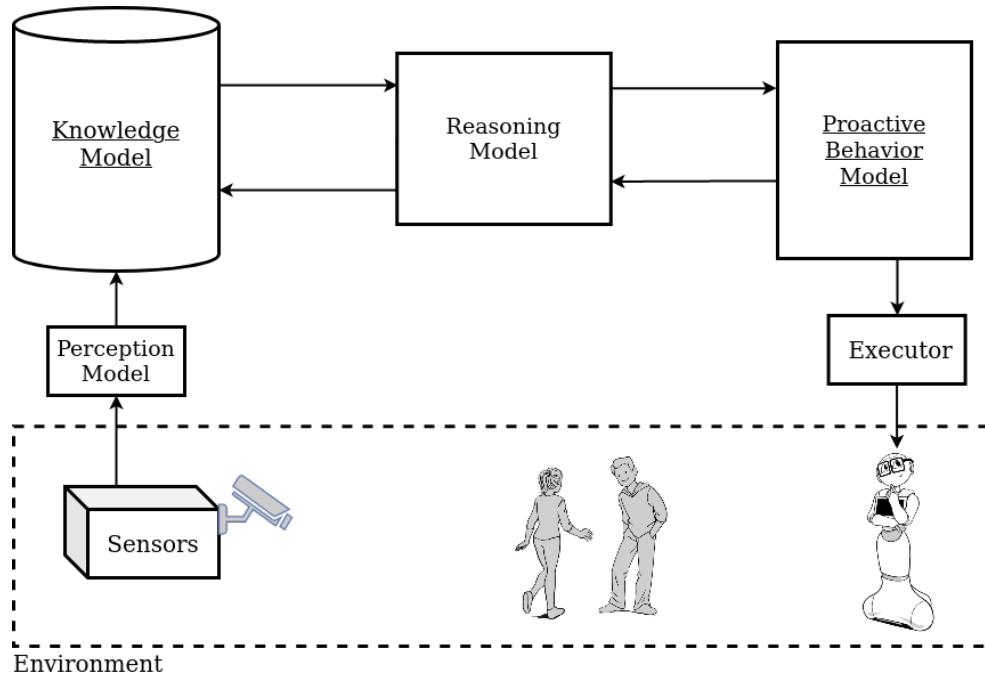


FIGURE 4.1: General overview of the proactive behavior generation is presented. It consists of five distinct models; Knowledge Model, Reasoning Model, Proactive Behavior Model for behavior generation, and Perception Model and Executor for creating the connection with the environment.

## 4.1 Knowledge Model

It is claimed that robots must reason about the current situation to initiate proactive behaviors. Set of knowledge about the current situation, such as desires and abilities of both robot and human enrich that reasoning. Different methods could provide this set of knowledge. In this thesis, symbolic representation with semantic annotation is chosen. The environment, different situations and desirabilities, set of goals, human desires, actions of robots and humans are represented symbolically and annotated semantically for understanding and keeping track of the knowledge.

Defining an environment still is one of the greatest challenges. It is hard to relearn the necessities of the environment from the start for every new change. Symbolic representation allows adding changes on the basis. According to desire, the environment could be defined manually from the start and continues with learning on its own, later. In this way, the base of knowledge could set it up. The robot could learn from the environment to increment or adapt its knowledge in advance. Enlargement of knowledge benefits the adaptation and sustainability of the robot for future changes. Since the knowledge of the robot is not needed to be reshaped, it will expand regularly.

The other benefit is that the base knowledge could change easily without modifying the initial working mechanism of the system. That means that system is not needed to be updated for each task. Generalization of the system supported by running different scenarios on the same system could be achievable by defining different tasks. The details of the environment are defined by using grouping principles of ontologies. Ontological principles create generic rules to define the environment. So, the relationship between each entity became visible.

Ontological principles of high-level symbolic representation of knowledge are mostly used to define complex knowledge related to each other. This framework inspires using the most common ontological principles to define knowledge. Previously, (Paléologue, 2019) proposed an ontology for interoperability. It adopts the different categories as social agents, physical objects, location, area, events, actions, and semantic templates. We are influenced by their definition of knowledge and adopt our categories. The storage of information in the knowledge model relies on an ontology principle. Chunks of information about the environment are stored in a symbolic context with semantic relationships between concepts. Pieces of knowledge connect together to create a model of the mental state of robot and a model of the person's mental state (Lemaignan et al., 2010). Relationships between objects, actions, subjects, predicates, and preferences described with RDF triples such as `< dish is_A food >`. Where `dish` and `food` represent the objects, and `is_A` is the predicates that represent the relationship between each other. In Figure 4.2, it is shown the how the objects and actions are linked with each other.

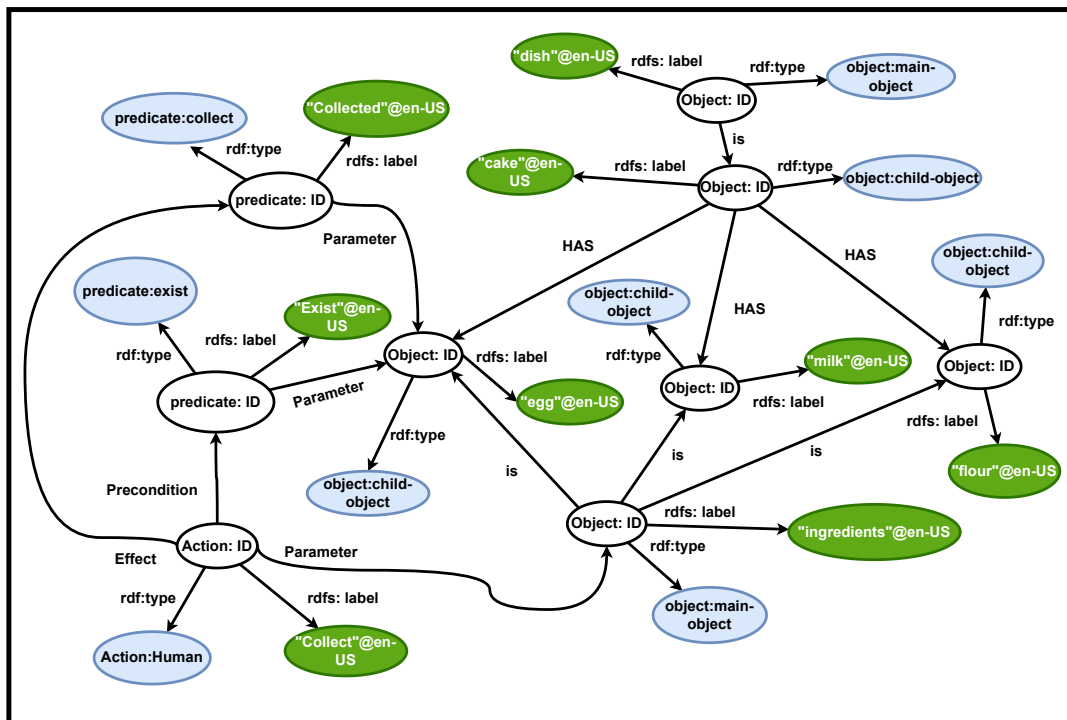


FIGURE 4.2: Demonstrating Symbolic Representation of Knowledge: This examples shows how the relationship sets between each entities. It is the partial examples baking cake recipes. The cake objects represented as a dish. Then, it shows the ingredient relationship of cake with egg, milk, flour. It also demonstrates specific action of <collect egg>. The action demonstrated with parameter: typed ingredient egg, precondition: exist with parameter egg, effect: collected with parameter egg.

Then, this knowledge is transferred into the planning domain definition language (PDDL) domain and problem. Creation of PDDL problem from symbolically represented knowledge is inspired from (Đurčák and Paralič, 2011). Đurčák and Paralič (2011) propose an architecture that creates a PDDL domain from an ontology web language (OWL) domain ontology. The architecture has two main points; definition of knowledge and transferring knowledge to the PDDL domain.

In our symbolic knowledge definition alongside agent and object definition, we define action and predicate as part of the PDDL domain definition. The majority of the PDDL rules are represented in the symbolic knowledge of the robot. In this way, we create a link between perception and reason via the knowledge of the robot.

Since the knowledge is specially defined, all information could be transferred into a planner. The related functions query all the knowledge entities and list them as a PDDL domain and problem. For example, actions are listed with their parameters, predicates, and effects. In Figure 4.3 demonstrates the same action both in the knowledge and PDDL domain.

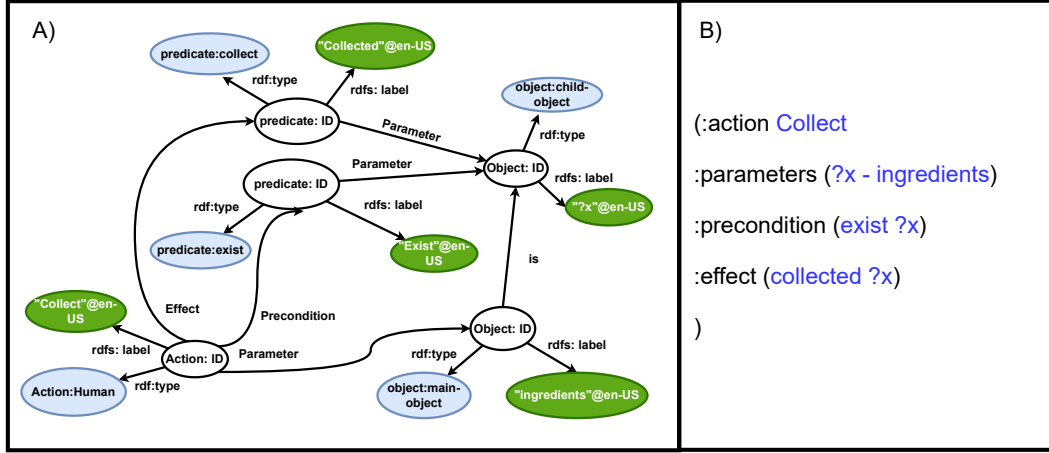


FIGURE 4.3: The figure consist of two parts. **Part A** shows how the generic collect action represented in knowledge. **Part B** shows how the knowledge turn into PDDL action style. The blue color of text represent the variables adapted from knowledge.

## 4.2 Reasoning Model

It is also claimed by other studies that to make proactive, interaction must be more socially acceptable in short to be proactive, it is important to recognize human intention, follow human's knowledge (Xue et al., 2020; Hansen and Bolander, 2020). In consideration of that, reasoning model has two main components; **planner model** which creates the plans for known goals, **human intent recognition model** which recognizes human intention from known goals.

### 4.2.1 Planner Model: Off-the-shelf Planner

The planner model aims to reduce the number of scripted inputs. We adopt an off-the-shelf planner to create a sequence of actions that lead to the goal state from the current state. *Fastdownward* is a domain-independent planner and uses planning domain definition language (PDDL). PDDL is a standard language to define domain problems in classical planning, which is defined by McDermott et al. (1998). It contains domain model that defines from the environment and problem model that defines current state. Problem models generated for both the human plans to reach their goals and the action plans of the robot are formulated in PDDL. The domain definition contains the predicates  $L$  used for describing states and the definitions of the available actions of humans  $U_H$ . The problem definition contains information about the available objects, the current states  $s_c$ , and the goal state of the problem  $g \in G_H$ . Planners are

optimized to find the shortest path between the current state  $s_c$  and the goal state  $s_g$ . As a result of planner usage, we get the shortest plan  $\theta_g$  to fulfill the goal from the current state. A plan of goal  $\theta_g$  includes the sequence of actions that should be fulfilled to reach  $s_g$  where all predicates of  $g$  are factual.

### 4.2.2 Reasoning about Human Intent

There are multiple ways to recognize the intention of the human. We select plan recognition being a straight-through logic-based approach for fully observable systems to reduce the adaptation efforts which will come to the change between different scenarios. This is why it is preferred to use the inverse planning method to recognize human intent.

In the literature of intention recognition, plan recognition is used as a tool for recognizing human intent (Han and Pereira, 2013; Persiani, 2020; Farrell and Ware, 2020). For reaching a goal, the planner determines sequences of actions. It would be efficient to use the same mechanism in the other direction can be used for human intention recognition, namely, by observing sequences of actions infer the human's plan intention to reach their goal (intention). The intention is the human's commitment to reach a goal. In plan recognition, it is assumed that the rational human is attempting to form optimal plans (Ramírez and Geffner, 2009), which could hint at their intentions.

The *Human Intent Recognition* module returns a set of intentions  $\mathcal{I}(s)$  of the human, that has been recognized in state  $s$ , according to the following formula:

$$\mathcal{I}(s) = \{\theta_{\hat{g}}(s) \mid \hat{g} \in \underset{g \in G_H}{\operatorname{argmin}}(\operatorname{len}(\theta_g(s)))\} \quad (4.1)$$

For each goal  $g$  in the set  $G_H$  of the potential human's goals, we use our planner to compute the shortest plan  $\theta_g(s)$  that the human can perform to reach  $g$  from the current state  $s$ . Then, we select the goal  $\hat{g}$  that leads to the shortest of these plans — or multiple  $\hat{g}$ s, if there are multiple globally shortest plans.  $\mathcal{I}(s)$  is the set of plans  $\theta_{\hat{g}}(s)$  corresponding to these goals.

The rationale behind this is that if there is only a short number of actions left to be executed in the full action sequence of a plan  $\theta_g(s)$ , then this means that the human already has done a large part of plan  $\theta_g(s)$ , hence, given that the human is rational, it is plausible to infer that the human intends to do all the rest of the actions in  $\theta_g(s)$  to reach  $g$  from  $s$ .

## 4.3 Proactive Behavior Model

There are different existing approaches to generate proactive communicative robot behavior. Some of the approaches focuses of proactivity of robot towards itself and the others focuses on proactivity of robot towards the human. In this thesis, we focus on 'What' question to generate proactive robot behavior from questions used for defining behavior (i.e. 'What', 'When', 'How'). As a initial step, plan-based reasoning model is developed to answer to generate proactive robot behavior. Then, rule-based reasoning process is developed for more on-the-point behavior generation to answer 'What' question of generation.

In our model, we are focusing on intention recognition from our system. The robot's knowledge and this reasoning result are proactive robot communication (see Figure 4.4).



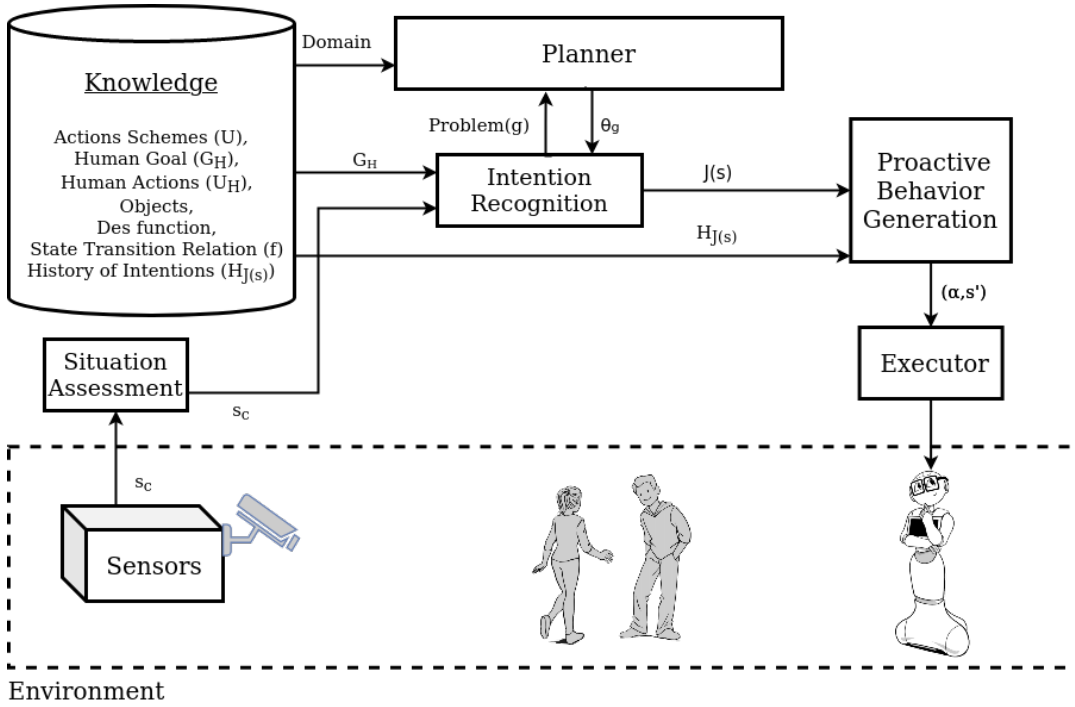


FIGURE 4.4: Model of Proactive Behavior Generation depends on the intention recognition

### 4.3.1 Proactive Behavior by Plan Based Model

As a naive initial step, we depend on the human intention recognition (defined in subsection 4.2.2) from the reasoning model. The most straight forward action to generate proactive behavior is using the action plan in intention once we detected the human intention. As it is shown in Figure 4.4, the reasoning model feeds the proactive behavior model. Since we are using the plan from the planner in the reasoning model, we have a list of actions that is inferred to realize in future. Then, it makes sense to enact first action from the list as a proactive action. Since we don't know any precedence of actions in the list.

Algorithm 1 generates the proactive behavior from the set of intentions  $\mathcal{I}(s)$  in state  $s$ , which gets from the intent recognition function defined in subsection 4.2.2. Proactive behavior generation from the recognized intention as; if the cardinality of the set of intentions is equal to 1, then the module returns the intention  $i(s) \in \mathcal{I}(s)$ , that is, the residual action plan  $\theta_g(s)$ . Then, return the first action  $(\alpha)$  of the intention  $i(s)$  to enact proactively. The action sequence can be directly enacted by the robot instead of the human, or the robot can communicate the actions to the human that they are supposed to do for reaching their goal. If the cardinality of the set of intentions is greater or less than 1, the intention is not recognized or ambiguous and hence an empty set is returned.

The example of communicating the actions is given from the example of human intention recognition. In previous section, it is presented that reasoning model have a list of intentions that recognized from human intention recognition. For example, if the human intention recognition list provides an intent with first action  $<(\text{collect water bottle})>$ . This action translated into a sentence as 'You should collect water bottle'. In this way, robot is reminding human to the objects needed to be collected before leaving the house. The template of the sentence is 'You should  $<predicate>$

$\langle \text{object} \rangle . '$  for an action composed of predicate and one object.

---

**Algorithm 1:** Plan-Based Proactivity ( $s, G_H$ )

---

```

1 if  $|\mathcal{I}(s)| = 1$  then
2    $i(s) \leftarrow \text{first}(\mathcal{I}(s))$ 
3    $\alpha \leftarrow \text{first}(i(s))$ 
4   return  $\alpha$ 
5 else
6   return  $\emptyset$ 

```

---

### 4.3.2 Proactive Behavior by Rule Based Model

The straightforward methods for generating proactive communicative robot behaviors are using the plan from the intention recognition. However, by using *plan-based methods* non-determined humans. Since, plan-based proactive behavior generation will be effective after the intention is determined. Majority of the time, intention recognition return more than one possible intention. We propose a *rule-based method* to cope with multiple intention. Rule-base methods are easy to define and point to the result. However, there are different ways to define the rules.

Some examples are using social rules that are used for reasoning about the situation. For example, such as greetings based on proxemics (Heenan et al., 2014), which is also known as proactive engagement, it is assumed that each human wants to interact with the robot within a close distance to the robot. So in this situation the robot action will be greeting the person before the person will interact with the robot. In that scenario, the rule is like when a human is detected, greet them. These common-sense rules do not effectively understand the actual situation in task-oriented scenarios. In reality, the human may not want to interact with the robot but wants to wait alongside. Therefore, the common-sense rules must be enriched with human-centered and task-oriented rules.

This section presents how we define the rules to generate proactive depending on the human intention and task definition. A rule-based system is developed to generate communicative suggestions depending on the human's task. Rules are selected based on the synthesis of the task's needs and the understanding of intention recognition. With the help of the rules, reasoning occurs to instantiate the parameters of the proactive suggestions.

Rule-based methods are crafted for the need of the specific task. The decision flow defined for generating proactive robot behavior. In this section, we define template

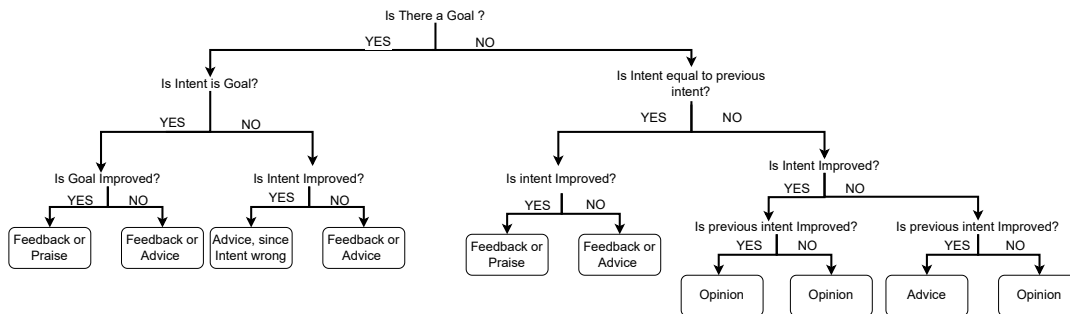


FIGURE 4.5: **Template of Specialized Rules** for generating proactive communicative robot behavior. Rules are dependent to the result of intention recognition and goal of the defined task.

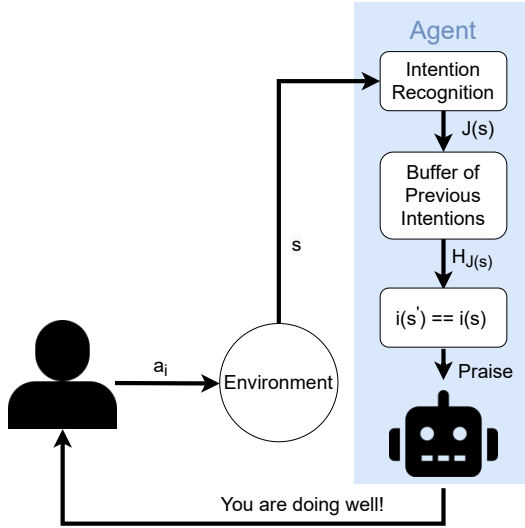


FIGURE 4.6: Praise Behavior Diagram of Working

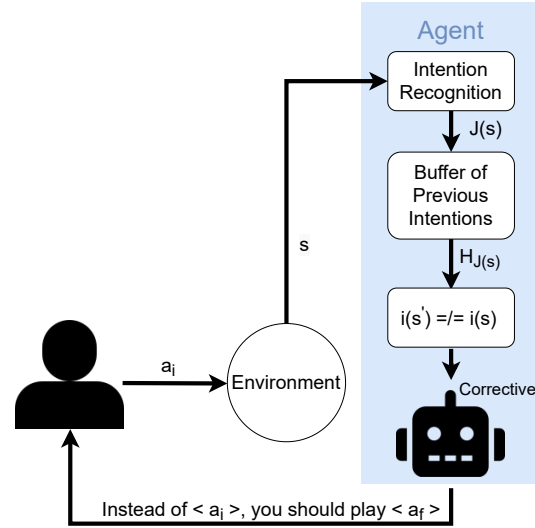


FIGURE 4.7: Corrective Behavior Diagram of Working

of decision flow of instantiating the proactive robot communication (aka proactive suggestion). The template is shown in Figure 4.5. This template is the representation of the handcrafted reasoning behind the proactive communication generation and adopting the principles of recognized human intention from reasoning module and set goal from the task definition.

The set of rules varies according to the need of the task. The tone of the proactive behavior slightly differs depending upon whether it is decided there is need of suggestion or feedback. In any cases, instantiating the proactive robot communication starts with intention recognition of the human actions. Intention recognition mechanism is defined in subsection 4.2.2. The intention recognition is providing the list of intentions or a single intention (in the same format which is  $\mathcal{I}(s)$  is the set of plans  $\theta_{\hat{g}}(s)$  corresponding to these goals) depending on the situation. Then, different type of proactive behavior is generated by using the information of the  $\mathcal{I}(s)$  and buffer (history) of previous intentions  $H_{\mathcal{I}(s)}$ . That's why the range of behavior generation method is defined. Those are;

**Praise** is also known as positive feedback, is the type of behavior that initiated praising sentences if the human played an action that will help him/her to reach the intent closer. The action initiated in the situations where current intent  $i(s)$ , determined from intention recognition, and previous intent  $i(s')$ , got from buffer of previous intentions, is equal to each other. Then, the communicative action of praise, one text from list of praise is initiated. The working diagram of praise action initiation is shown in Figure 4.6.

**Corrective Behavior** is also known as feedback that will extract the action to correct the human's action. It is instantiated to cope with the situations where the human had an intention and the human's current action is not part of the human's previous intention. This lead that the human's current intention is different than human's previous intention. Then, robot enact an actions to apply for correcting the action of the human. At the end, the template looks like; "Instead of <current action>, you should <selected action>". The working diagram of corrective action initiation is shown in Figure 4.7.

**Advice** extract the action to used in situations when robot detects an ultimate

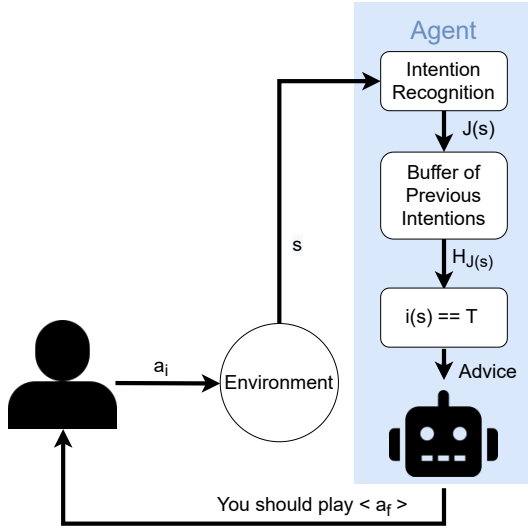


FIGURE 4.8: Advice Behavior Diagram of Working

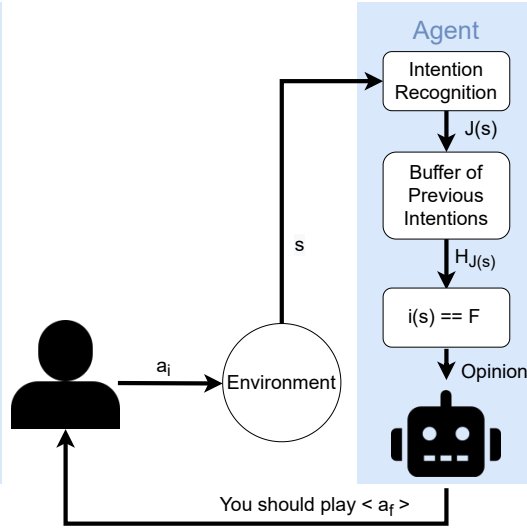


FIGURE 4.9: Opinion Behavior Diagram of Working

intention of human ( $i(s)$ ), which means there is only one intention in  $\mathcal{I}(s)$  and denoted by  $i(s) == T$ . The action help the human for future actions instead of praising the human. The action uses the sentence template "You should <selected action>" to generate the communicative action. Selected action is the reasoned from  $\mathcal{I}(s)$ . The working diagram of advice action initiation is shown in Figure 4.8.

**Opinion** extract the action to used in situations when robot **not** detects an ultimate intention of human ( $i(s)$ ), which means there is only one intention in  $\mathcal{I}(s)$  and denoted by  $i(s) == F$ , but still wants to help human to proceed. The action uses the sentence template "You should <selected action>" to generate the communicative action. In this action type, the selected action is reasoned from  $\mathcal{I}(s)$ . It is either the most popular action from the goal list or the  $\mathcal{I}(s)$ .

It is defined how a robot should generate its proactive communicative behavior. In above, it is only mentioned rule-based creation of the behavior by using the result of an intention regulation and the task-oriented behavior. However, the rule creation could have added other metrics such as long pauses between each action, etc. Thus, the template decision tree shows that even the rules depending on only the two scales intent - what is the human current trying to achieve? - or goal - what is the set by task, human should achieve? -, the decision tree leveled and branched a lot because of the combination of these two scales.

There is also **Suggestive Behavior**. Suggestive Behavior is similar to the *Advice* action. Thus, *Suggestive Behavior* extract an action in situations when the human takes too much time to pursue an action. Then, if the robot able to recognize an ultimate intention of human ( $i(s)$ ) from the given state, which means there is only one intention in  $\mathcal{I}(s)$  and denoted by  $i(s) == T$  then the robot proactively select an action to enact. The action uses the sentence template "You should <selected action>" to generate the communicative action. Selected action is the reasoned from  $\mathcal{I}(s)$ . The working diagram of suggestive behavior initiation is shown in Figure 4.10.

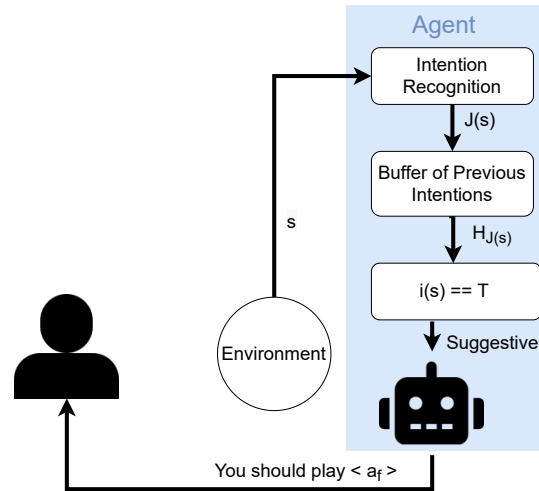


FIGURE 4.10: Suggestive Behavior Diagram of Working

## 4.4 Conclusion

In summary, this chapter presented a framework for generating proactive communicative robot behavior with a plan-based and a rule-based proactive behavior models. Proposed framework aims to answer to the question of ‘**What** kind of proactive behavior must be initialized?’. Proposed framework is the combination of different models to offer a generic reasoning mechanism to generate proactive behavior. That’s why the focus is on knowledge model, reasoning model and proactive behavior model.

The knowledge model offers unified definition of environment that planner of reasoning model could use. This is linked with intention recognition component that is using the planner. In this way, it is not needed to retrain the intention recognition model, since it automatically adapt the changes from the planner and planner is adapting to the knowledge definition. This loop ends with feeding proactive behavior model with result of intention recognition.

Proactive behavior generation is presented by the plan-based model and rule-based model. Both ways has their own pros and cons. *Plan-Based Model* is adaptable to all systems and any type of input, however; it is not always answer the demand of the system. On the other hand, *Rule-Based Model* is needed to be modified for each task and crafted again for the type of rule according to the expectation of the task, so they could be more agreeable with the system needs.

Thus, in the proposed framework, we give only human intention recognition as a reasoning model. That is an demonstration of that the different reasoning models could be added as a separate component. As a result of this, proactive behavior generation model is needed to be update to cope with all reasoning mechanisms.

## Chapter 5

# Proactive Behavior by Equilibrium Maintenance Model

*' You can lead a man to Congress, but you can't make him think. '*

Milton Berle

In Chapter 4, we present a framework to generate proactive robot behavior from the human intention recognition. The proposed framework has plan-based reasoning for generating proactive behaviors and has limitations of only answering '**what**' question of behavior description. To answer the '**when**' question, we decided to merge our intention based proactive generation framework with predictive based Equilibrium Maintenance (EqM) from Grosinger et al. (2019). In this chapter, we propose two methods to integrate those two methods, *Parallel Integration Method* (PiM) and *Sequential Integration Method* (SiM), answers to '**what**' and '**when**' question.

To understand the most important contribution of this Chapter, i.e., an integration of intention-based and predictive proactivity, we need to introduce the individual systems it is based on. Therefore, we present a system model PiM to generate proactive robot behavior in parallel, which is presented in Figure 8.3, in Section 5.1; then, we present a an intention-based robot proactivity HIRR in Section 5.2; next we summarize the previously introduced work on equilibrium maintenance EqM in Section 5.3; finally, we propose a parallel integration of HIRR and EqM, PiM in Section 5.4. Then, we introduce our naive approach to integrate those two system in SiM, sequentially at the earlier phases of action generation in Section 5.5.

### 5.1 System Definition

In order to combine intention based proactive framework (HIRR) that proposed in subsection 4.3.1 and predictive proactivity, Equilibrium Maintenance (EqM), in parallel way, we propose the system called PiM for parallel integration method, that is represented in Figure 8.3.

The system includes different components to offer a fully autonomous interaction, namely: a situation assessment component, a knowledge component, a planner component, an intention-based proactivity component, a predictive proactivity component, an action selection component and lastly an executor component.

The **situation assessment** and the **executor** components act as front-ends to the physical environment. They respectively collect and generate changes from/to the environment.

To model the **environment** and its dynamics we consider a standard dynamic system  $\Sigma = \langle S, U, f \rangle$  where  $S$  is a set of states,  $U$  is a finite set of external inputs

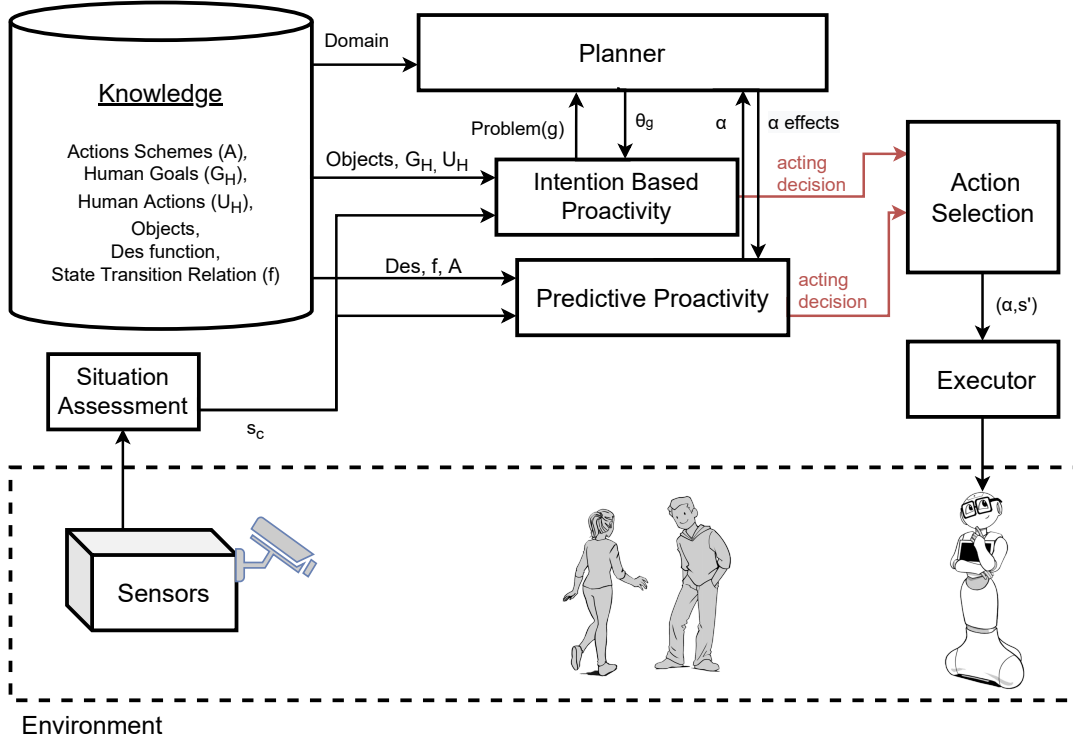


FIGURE 5.1: **Parallel Integration Method (PiM)**; that merge two system intention based proactivity (HIRR) and predictive proactivity (EqM)

(robot actions or human actions) and  $f \subseteq S \times U \times S$  is a transition relation. The system's dynamics is modeled by the relation  $f(s, u, s')$ , which holds iff  $\Sigma$  can go from  $s$  to  $s'$  when input  $u$  is applied in  $s$ . To give  $S$  a structure, we rely on a symbolic representation of world states. Given a finite set  $\mathcal{L}$  of predicates, we let  $S \subseteq \mathcal{P}(\mathcal{L})$ , and denote by  $s_c$  the current state. Each state  $s \in S$  is thus completely determined by the predicates that are true in  $s$ . Let then  $G_H \subseteq S$  be the set of human goals. Each goal  $g \in G_H$  is determined by predicates that are true in  $g$ . Given a goal  $g$ , we denote by  $s_g$  any state in  $S$  where all predicates in  $g$  (and potentially more) are true, hence  $g \subseteq s_g$ . We also denote by  $S_g \subseteq S$  the set of all states  $s_g$  where the predicates of  $g$  are true.

The **knowledge** component represents a model of the environment, including the above elements. This model encodes the state evolution of the world, the set of goals of the human, action plans of how the human can reach their goals, robot capabilities as a set of action schemes, the state transition function and a desirability function to compute the degree of desirability of a state.

The **planner** component is an off-the-shelf planner able to create a sequence of actions that lead from the current state to the goal state. The planner is defined in subsection 4.2.1.

The **intention-based proactivity** component and the **predictive proactivity** component are both able to generate proactive behavior, but they use two different methods which we describe below: human intention reasoning from Chapter 4 and equilibrium maintenance (Grosinger et al., 2019), respectively.

Finally, the **action selection** component integrates the decisions generated by those two methods into an ultimate proactive behavior for execution. These last three components constitute the core contribution of this chapter, and they are described in



deeper detail in the following sections.

## 5.2 Intention Based Proactivity: Human Intention Recognition and Reasoning

For doing the intention based reasoning on proactivity, we define *Human Intention Recognition and Reasoning* (HIRR) model to generate proactive behavior based on intention recognition, which is adopted from the proposed framework in chapter 4. The HIRR model has two functionalities which is adopted; *Human Intent Recognition* and *Planning Based Proactive Behavior Model*. *Human Intent Recognition* is described in subsection 4.2.2, returns the human intention by applying inverse planning rules. *Planning Based Proactive Behavior Model* generates the proactive behavior from the recognized intention for the robot, which is described in subsection 4.3.1, can then *proactively* enact the next action in the action plan (intention) of the human on behalf of the human, or it can inform the human which action to take next in order to reach their goal.

## 5.3 Predictive Based Proactivity: Equilibrium Maintenance

For doing reasoning on proactivity in the current work we employ a model and framework called *Equilibrium Maintenance* as described in Grosinger et al. (2019). Here, we only give a brief overview of the framework while the interested reader is referred to the cited reference for details.

We consider a standard dynamic system  $\Sigma = \langle S, U, f \rangle$  where  $S$  is the set of states,  $U$  is a finite set of external inputs (robot actions) and  $f \subseteq S \times U \times S$  is the transition relation. Each state  $s$  is completely determined by the predicates that are true in  $s$ . The system's dynamics are modeled by  $f(s, u, s')$  which holds iff  $\Sigma$  can go from  $s$  to  $s'$  when input  $u$  is applied in  $s$ . The free-run behavior  $F^k$  of  $\Sigma$  determines the set of states that can be reached from  $s$  in  $k$  steps when applying the null input  $\perp$ . This models the evolution of the system when no robot actions are performed.

$$\begin{aligned} F^0(s) &= \{s\} \\ F^k(s) &= \{s' \in S \mid \exists s'' : f(s, \perp, s'') \wedge s' \in F^{k-1}(s'')\}. \end{aligned}$$

Des is a fuzzy set of  $S$ . Membership function  $\mu_{\text{Des}} : S \rightarrow [0, 1]$  describes the degree to what a state  $s$  is desirable. We extend the definition to sets of states  $X \subseteq S$ , that is,  $\mu_{\text{Des}}(X) = \inf_{s \in X} (\mu_{\text{Des}}(s))$ . In the following, we abbreviate  $\mu_{\text{Des}}(\cdot)$  as  $\text{Des}(\cdot)$ .

Action schemes are partial functions:

$$\alpha : \mathcal{P}(S) \rightarrow \mathcal{P}^+(S),$$

that allows us to capture that states can be brought into other states by robot acting. An action scheme  $\alpha$  abstracts all details of action:  $\alpha(X) = Y$  only says that there is a way to go from any state in the set of states  $X$  to some state in set of states  $Y$ . Action schemes can be at any level of abstraction, from simple actions that can be executed directly, to sequential action plans, or policies, or high level tasks or goals for one or multiple planners. We denote with the *benefit* the degree to what the effects of applying an action scheme are desirable.

$$\text{Bnf}(\alpha, s, k) = \inf_{X \in \text{dom}(\alpha, s)} \text{Des}(F^k(\alpha(X))), \quad (5.1)$$



where  $F^k(X) = \bigcup_{s \in X} F^k(s)$  and  $\text{dom}(\alpha, s)$  is the domain of  $\alpha$  relevant in  $s$ . Based on these definitions, we define different types of *opportunity* for acting. These are at the foundation of proactivity through equilibrium maintenance.

$$\begin{aligned}
\text{Opp}_0(\alpha, s, 0) &= \min(1 - \text{Des}(s), \text{Bnf}(\alpha, s)) \\
\text{Opp}_1(\alpha, s, k) &= \min(1 - \text{Des}(s), \sup_{s' \in F^k(s)} (\text{Bnf}(\alpha, s'))) \\
\text{Opp}_2(\alpha, s, k) &= \min(1 - \text{Des}(s), \inf_{s' \in F^k(s)} (\text{Bnf}(\alpha, s'))) \\
\text{Opp}_3(\alpha, s, k) &= \sup_{s' \in F^k(s)} (\min(1 - \text{Des}(s'), \text{Bnf}(\alpha, s'))) \\
\text{Opp}_4(\alpha, s, k) &= \inf_{s' \in F^k(s)} (\min(1 - \text{Des}(s'), \text{Bnf}(\alpha, s'))) \\
\text{Opp}_5(\alpha, s, k) &= \min(\sup_{s' \in F^k(s)} (1 - \text{Des}(s')), \text{Bnf}(\alpha, s, k)) \\
\text{Opp}_6(\alpha, s, k) &= \min(\inf_{s' \in F^k(s)} (1 - \text{Des}(s')), \text{Bnf}(\alpha, s, k))
\end{aligned}$$

For example, the minimum out of comparing (1) the degree to what the current state  $s$  is undesirable, and, (2) the benefit of acting now, gives the degree to which an action scheme  $\alpha$  is an opportunity of type  $\text{Opp}_0$  in state  $s$  with look-ahead 0. Another example: the minimum out of comparing (1) the maximum future undesirability of states, and, (2) the benefit of acting now, gives the degree to which an action scheme  $\alpha$  is an opportunity of type  $\text{Opp}_5$  in state  $s$  with look-ahead  $k$ .

Finally, we can define what it means for a system to be in equilibrium.

$$\text{Eq}(s, K) = 1 - \sup_{k, i, \alpha} \text{Opp}_i(\alpha, s, k), \quad (5.2)$$

for  $k = 0, \dots, K, i = 0, \dots, 6, \alpha \in A$ , where  $A$  is the set of all action schemes. In words, equilibrium is the complement of the maximum opportunities - if there are big opportunities, then the system is very much out of equilibrium, if there are small opportunities then the system is close to being in equilibrium, if there are no opportunities at all, then the system is fully in equilibrium. The notion of equilibrium is used in the equilibrium maintenance algorithm EqM to achieve agent proactivity (see Algorithm 2).

---

**Algorithm 2:** EqM( $s, K$ )

---

```

1 if Eq( $s, K$ ) < 1 then
2   | Opps  $\leftarrow \arg \max_{k, i, \alpha} (\text{Opp}_i(\alpha, s, k))$ 
3   |  $\langle \alpha, s', \text{Opp}_i, k, \text{oppdeg} \rangle \leftarrow \text{choose}(\text{Opps})$ 
4   | return  $\langle \alpha, s', \text{Opp}_i, k, \text{oppdeg} \rangle$ 
5 else
6   | return  $\langle \rangle$ 

```

---

## 5.4 Parallel Integration Method: Integration of Human Intention Recognition and Reasoning and Equilibrium Maintenance

In this section, it is defined how to define PiM, parallel integration method, to integrate HIRR and EqM. HIRR and EqM are complementary approaches that create proactive acting in different ways. PiM has the action selection component that

integrates the approaches at the result phase, after each system has proposed their proactive actions. However, each approach has a different reasoning mechanism and affects the future states in different ways. The HIRR system infers proactive action by interpreting the past and current system state. HIRR is based on supporting the human towards reaching their intention. It infers the human's intention and suggests a sequence of actions to reach the human's goal starting from the current state.

Integrating the two systems in parallel is not trivial. Consider an example where, in a given state  $s$ , there is an opportunity to warn the human for hail,  $\text{Opp}_5(\alpha_{\text{warn}}, s, 2)$ , and at the same time HIRR infers to bring the compass to the user as the recognized human intention is to go hiking because the human has gathered the backpack, then we have two opposing goals for robot acting. We have to measure them and make them comparable. We propose a solution for integrating the two systems EqM and HIRR by turning the HIRR goal into an opportunity of type  $\text{Opp}_0$ , hence,  $\text{Opp}_0(\alpha_{\text{collect}(\text{compass})}, s, 0)$  and check its degree, that means, see how beneficial its effects are when applied, or in other words, how desirable the states are it can achieve when applied. Since both models aim to predict and affect future states and both address this question of proactive action in complementary ways, it makes sense to combine the two. Hence, action selection is used for combining the two systems, HIRR and EqM, that is, the proposed ways of robot acting are collected in a pool, out of which the merged system chooses the best acting alternative.

However, the two systems do not share the same way of modeling acting decisions. The EqM system models acting alternatives as opportunities of different types where the robot should perform acting now or in the future. In HIRR, on the other hand, the proposed acting decision is modeled as a sequence of actions to be executed immediately. There exists one opportunity type that captures acting immediately to achieve immediate benefit, that is,  $\text{Opp}_0$ . Hence, it makes sense to transform the result of HIRR into an opportunity of such type.

We choose to transform the acting decision of HIRR into an opportunity of type  $\text{Opp}_0$  because this opportunity type represents the acting decision of HIRR best. HIRR's proposed acting decision is based on the current state and is modeled as a sequence of actions to be executed immediately; appropriately  $\text{Opp}_0$  means to act immediately, based on reasoning on the current state. Since both systems, HIRR and EqM, aim to predict and affect future states and both address this question of proactive action in complementary ways, it makes sense to combine the two. Hence, we use a late combination for joining HIRR and EqM. This means, the proposed ways of robot acting are collected in a pool, which is done in the Action Selection component (Figure 8.3), out of which the merged system chooses the best acting alternative.

When transforming an HIRR acting decision into an opportunity of type  $\text{Opp}_0$  it is necessary to modify the outcome of the Des-function temporarily. The Des-function is a part of EqM and therefore ignorant of human intention in its current status. It is ignorant of modeling unfulfilled human intentions as undesirable and fulfilled ones as desirable. Such a Des-function would therefore not generate an opportunity when the human has not reached their goal and has their intention unfulfilled. By temporarily decreasing the desirability of the current state (Algorithm 3, line 5) modeling the undesirability of unfulfilled intention, and temporarily increasing the desirability of the effects of acting on the intention (Algorithm 3, line 6), which is proactive acting towards fulfilling the human intention, we compensate this issue and allow the generation of an opportunity based on human intention recognition and reasoning.

The default setting of the Des-function, with which EqM runs, therefore is modified temporarily when a human intention is recognized. For example, a state ( $s$ ) that would have desirability,  $\text{Des}(s) = 0.7$  with or without recognized human intention. The desirability of the effects that would manifest when action (by the human or the robot) would be enacted – following the human’s intention –, on the other hand, is enhanced, which would not be the case otherwise when no human intention was recognized, e.g., with recognized human intention  $\text{Des}(\alpha(s)) = 0.9$ , without recognized human intention  $\text{Des}(\alpha(s)) = 0.7$ .

---

**Algorithm 3:** Transform HIRR-result to Opp

---

```

1 // Save intention, i.e., action plan inferred by intention recognition as action scheme
2  $\alpha(s) \leftarrow \text{HIRR}(s, G_H)$ 
3 if ( $\alpha \neq \perp$ ) then
4   // Decrease desirability of states without new effects of human intention's acting
   // and increase desirability of states with new effects of human intention's acting
5    $\text{Des}'(s) \leftarrow \text{decrease}(\text{Des}(s))$ 
6    $\text{Des}'(\alpha(s)) \leftarrow \text{increase}(\text{Des}(\alpha(s)))$ 
7   // Compute the degree of the opportunity
8    $\text{oppdeg} \leftarrow \min(1 - \text{Des}'(s), \text{Bnf}'(\alpha, s))$ 
9   return  $\langle \alpha, s, \text{Opp}_0, 0, \text{oppdeg} \rangle$ 
10 else
11   return  $\langle \rangle$ 
```

---

The purpose of Algorithm 3 is to transform the result of human intention recognition and reasoning – an activity to proactively be executed by the robot – into an opportunity for acting so that it can be compared to opportunities coming from EqM. How the decrease- and the increase-function (Algorithm 3, lines 5 – 6) are to be implemented in detail is an open question. In this paper we choose a fixed value to decrease state desirability and the same fixed value to increase effect state desirability.

In Algorithm 3, line 8, the formula for computing an opportunity of type  $\text{Opp}_0$  is used with the modified desirability function  $\text{Des}'(s)$  and the benefit function based on the modified desirability function,  $\text{Bnf}'(\alpha, s)$ . This gives the degree of the opportunity based on human intention reasoning,  $\text{oppdeg}$ . Finally, in line 9 of Algorithm 3, the opportunity is returned, comprising its action scheme  $\alpha$ , that is, the action plan returned from Algorithm 1 in line 4, the current state  $s$ , the type of opportunity  $\text{Opp}_0$ , the temporal look-ahead, 0, and the degree of the opportunity,  $\text{oppdeg}$ .

Now that we have opportunities for acting based on reasoning on prediction returned from Algorithm 2 and based on reasoning on human intention returned from Algorithm 3, we can finally select which of them to enact in Algorithm 4. In an endless loop the *Action Selection* does the following: first the current state is detected (Algorithm 4, line 2), and an empty set for opportunities,  $\text{Opps}$ , is created (Algorithm 4, line 3). If the state has changed (Algorithm 4, line 4), then the set  $\text{Opps}$  collects the opportunities for acting coming from both proactivity systems,  $\text{EqM}(s, K)$  and  $\text{HIRR}(s, G_H)$  (Algorithm 4, lines 6 – 7). Note that this means that generating proactive behavior in our algorithm is driven by state change, be it by changes in the environment or by application of robot action. In Algorithm 4, line 8, *Action Selection* chooses one opportunity out of the pool of opportunities from both systems EqM and HIRR. Thereby we have a means to compare the goal coming from EqM, for example,  $\text{Opp}_5(\alpha_{\text{warn}}, s, 2) = \text{oppdeg}_{\text{EqM}}$ , and the goal coming from HIRR, for example,  $\text{Opp}_0(\alpha_{\text{collect}(\text{compass})}, s, 0) = \text{oppdeg}_{\text{HIRR}}$ . The function  $\text{choose}()$  in Algorithm 4 works like the function  $\text{choose}()$  in Algorithm 2, which is the  $\text{choose}()$

in (Grosinger et al., 2019). The `choose()` function selects the opportunity with the highest degree to be enacted. If there are several opportunities with highest degree a decision is made by the opportunity type, how much benefit can be achieved and the size of the look-ahead. We refer to (Grosinger et al., 2019) for details. In the last line of Algorithm 4, line 10, the selected action of the chosen opportunity is dispatched to an executive layer to be enacted.

---

**Algorithm 4: Action Selection**


---

```

1 while true do
2    $s \leftarrow$  current state
3    $\text{Opps} \leftarrow \{\}$ 
4   if  $s$  has changed then
5     // Find opportunities for acting from both HIRR and EqM
6      $\text{Opps.add}(\text{EqM}(s, K))$ 
7      $\text{Opps.add}(\text{HIRR}(s))$ 
8      $\langle \alpha, s', \text{Opp}_i, k, \text{oppdeg} \rangle \leftarrow \text{choose}(\text{Opps})$ 
9     // Dispatch chosen opportunity
10     $\text{dispatch}(\alpha, s')$ 

```

---

## 5.5 Sequential Integration Method: Integration of Human Intention Recognition and Reasoning and Equilibrium Maintenance

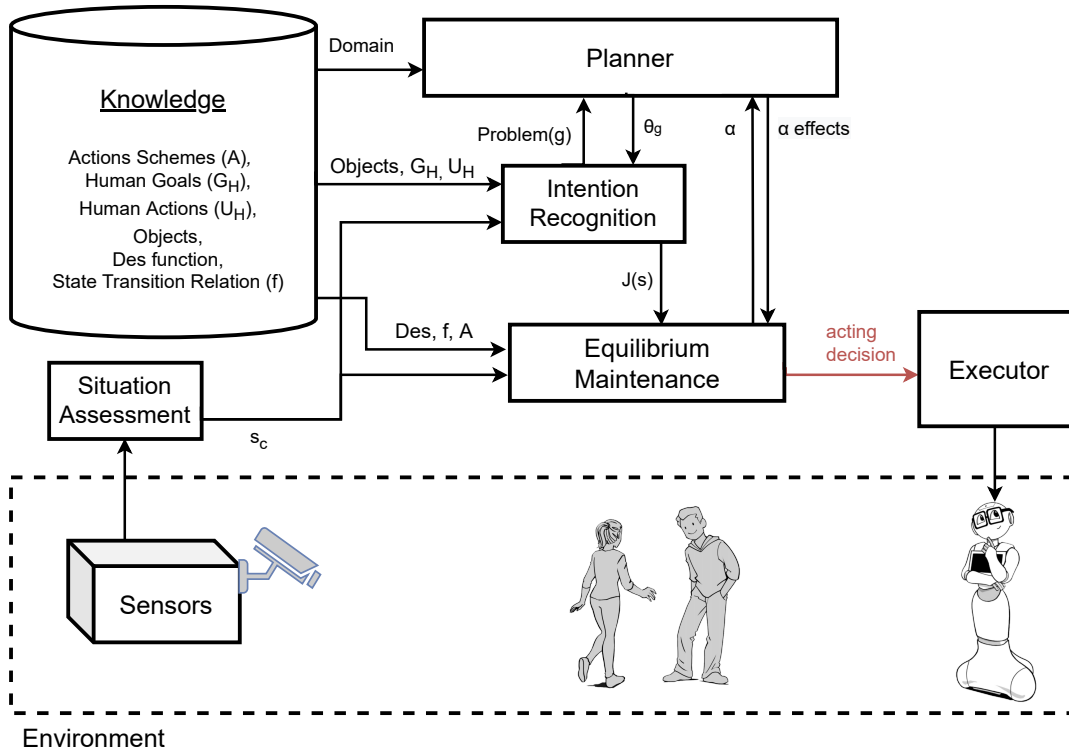


FIGURE 5.2: **Sequential Integration Method (SiM)**; that merges two system intention based proactivity (HIRR) and predictive proactivity (EqM)

In previous section, we explore how to integrate EqM and HIRR in parallel method (PiM), that is depending on the final result of EqM and HIRR. However, integration on the last step could have created a confusion about selection process. For example, if the human's intention creates an undesirable situation at the end, the action selection mechanism could realize that very late. This is not an optimal solution. In this section, we explore how to integrate those two systems in sequential method (SiM), which means integration in earlier phases of proactive behavior.

In PiM, we translate proposed proactive action of HIRR into opportunities of EqM. In SiM, we are expecting that opportunities of EqM already generates intention based proactive actions. To do that, different aspects of EqM is affected by result of intention recognition component, which is defined in subsection 4.2.2. In order to integrate EqM and HIRR in sequential way, we propose a system called Sequential Integration Method (SiM), that is represented in Figure 5.2.

### 5.5.1 Desirability Function

Before explaining the changes on the system, we wanted to highlight how we adapted to used the Des-function and state evolution map. The Des-function is used for calculating the desirability of the each state from the known undesirable situations. The undesirable situations are listed with their conditions and coefficients. Des-function is given in Equation 5.3. In equation 5.3,  $\rho$  refers to each coefficient of undesirable situation. Probability of each condition is occurring on the state is represented by  $\sigma$ .  $\sigma$  either could be 1, if all conditions are met, or 0 if all conditions are not met.

$$\text{Des}(s) = \prod_{\forall U_{undes}} [(\sigma) + \rho(1 - \sigma)], \quad (5.3)$$

$$\sigma \rightarrow \{0, 1\} \quad (5.4)$$

### 5.5.2 Changes of Desirability Function

In this section, we present the integration of intention recognition into the EqM system. We modified the Des-function that run on the whole system to adapt the changes of intent recognition. It is mentioned earlier that the desirability of the state is used for proposing opportunities. If the states are in maximum desirability - when there is no undesirable situation in the state such as raining, etc. -, opportunities do not generated. The Des-function will be modified dynamically according to the result of intention recognition. In this way, opportunities to satisfy the human intention should be generated on its own through the EqM. Initially Des-function defined for reasoning a list of undesirable situations. It is assumed that all states are desirable at the beginning. Then, it is checked if state includes any of undesirable situation. If the state has any of those undesirable situations, desirability value multiplied by the value of undesirable situation. To update the Des-function, we created a dynamic variable called *degree*. *degree* variable is manipulated by the function that manipulates state desirability dynamically according to status of intention recognition. The function stores the plan of each intention and effect value to update.

$$\text{degree} = (\text{severityInState} / \text{sizeOflist}) \quad (5.5)$$

Then *degree* variable is generated to determine how to effect each state. From the equation 5.5, an undesirability value is calculated by severity of intention list's

element occur in state. Then, we extracted from one to increment desirability towards the intended goal. It start with lower desirability and gets higher when it gets closer to the intended goal. For example; If the state has only one element from the intention that has 5 element, then the degree calculated as 0.2. If the state has three element from the same intention, then the calculated degree is 0.6. Calculated degree later used for adjusting the desirability value of the state. In this way, it is prevented to have same state desirability for path of states to indented goal. In this way, it gives us a inclining desirability value towards the goal state.

This method allows actions that is beneficial to the intentions initiated as opportunities. Since desirability value dynamically updated according to *degree* variable that calculated by the human's intention.

### 5.5.3 Further Optimizing for Reasoning

In the SiM, we take further actions for optimizing the reasoning mechanism. To improve the quality of the opportunity calculation. We create a state evolution map to enlarge the reasoning perspectives. As a difference from classical EqM calculations, we created a probabilistic state evolution map, that will be created dynamically. This means that evolution map consider all possibilities of changes that could be occurred from the start state. This leads to excess amount of calculation, to be specific (each state x each state) for each K alongside with calculation of unnecessary opportunities. EqM will be eager to prevent the user reach to undesirable state even the user is not intended to be there. The purpose of Algorithm 5 is to prune the states that are not related with intention of the user. The pruning occurs only in the first step look ahead to keep the opportunities for possibilities of intention changes. We keep the pruning for the first look up state only, to keep the others options for non-rational decisions. In that case, if the intention divert in later stages, the evolution map still be functional.

---

#### Algorithm 5: Pruning of Evolution Map

---

```

1 // Set the evolution map, current state & list of element of intention
2  $s \leftarrow \text{return-current-state}()$ 
3  $\text{evolveMap} \leftarrow \text{return-evolve-map}()$ 
4  $\text{intentList} \leftarrow \text{return-intent-plan}()$ 
5 for each state in  $\text{evolveMap}[s]$  do
6   if state is not include any of elem in  $\text{intentList}$  then
7     // If state includes any element from intention, remove the state from the list of
       future states of
8      $\text{evolveMap}[s].\text{remove}(\text{state})$ 
9 // Return updated  $\text{evolveMap}$ 
10 return ( $\text{evolveMap}$ )
```

---

Another problem is setting a constant variable to how far should EqM consider for a realistic reasoning about the future changes. The most common usage in past of of EqM is to set  $K = 2$ , to look 2 state ahead to be proactive in (Grosinger et al., 2019). Then, the question raised for do can we be sure about 2 time looking ahead will give us the reliable result. Should the system looks for further states. The state of K determined by length of intention. The usage of length of intention shows that (at least in one state in state evolution map) the intention is satisfied at the end of the look ahead, so any problematic situation could able to predict beforehand. This also shows that K become dynamic. In earlier stages most likely K is larger than 2. Toward

the reach of the goal  $K$  becomes 1 and sometimes 0 according to the situation of reaching the goal. We are aiming to provide a flexible framework that could forecast about the result of the indented goal. For example, if the result of the intention will be catastrophic for the human, it would be better not to start from the beginning. However, we are not able to see that result in every 2 state frame if the completing the goal take more than 2 state. It is believed that dynamic  $K$  could tackle with that problem and have a better reasoning about the consequences of the intentions.

As a result of all changes, system works as in Algorithm 6. When the current state is changed, first HIRR recognizes the intention of the user. Respectively,  $K$  set dynamically and state evolution map pruned by the recognized intention. Till now, the running process is the part of the Stage 2 of integration. Then, it follows with Stage 1 of integration, either by combining opportunities or by modifying Des-function, system finds the opportunities and dispatch the chosen opportunity.

---

**Algorithm 6:** HIRR and EqM combined system

---

```

1 while true do
2    $s \leftarrow$  current state
3    $evolveMap \leftarrow$  return-evolve-map()
4   if  $s$  has changed then
5     // Find intent HIRR
6      $intentList, intentLength \leftarrow$  HIRR( $s$ )
7     // Set  $K$  with the length of intent
8      $K \leftarrow intentLength$ 
9     // Prune evolve map
10     $evolveMap \leftarrow$  prune( $s, evolveMap, intentList$ )
11    //Merged EqM, Stage 1
12    combinedEqm( $(s, K, evolveMap)$ )

```

---

## 5.6 Conclusion

In this chapter, we presented the integration of intention based proactivity framework (defined in chapter 4) and predictive proactivity from (Grosinger et al., 2019). We proposed two ways of integration; *PiM*, *parallel integration method* and *SiM*, *sequential integration method*. *PiM* framework is a part of the study that is submitted to Frontiers Robotics and AI Journal and present in later in chapter 8.

*PiM*, parallel integration method, is the straight-forward approach to combine EqM and HIRR, in parallel. For the integration, we adopt intention based proactivity from the previously proposed framework, by combining the components of human intent recognition (see in subsection 4.2.2) and plan based proactive behavior model (see in subsection 4.3.1) and named it as *Human Intention Recognition and Reasoning* (HIRR). In this way, the result of both framework could be seen clearly. Then, *Action Selection* component collects the proposed proactive behaviors of both approaches (HIRR & EqM) to compare and select the best proactive behavior to enact.

Alongside with *PiM* approach, we propose *SiM*, sequential integration method, to define the integration of system in early stages. The reason behind the definition of *SiM* is to have system integration be more autonomous on reasoning. Since it is already showed that the straight forward *PiM* is worked (details presented later in Chapter 8). So, instead of proactive actions related to intention recognition initialized by HIRR, we modify the desirability of the system, proactive actions initialized by EqM. Then, we propose an optimization strategy on state evolution map and further

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reasoning. Both SiM and PiM are the extended version of the proactive robot behavior generation framework that presented on Chapter 4.





## **Part III**

# **Experiments**



## Chapter 6

# Recipe Task

The study in this chapter was published in the workshop of Creativity and Proactivity at ICSR 2020.

### 6.1 Research Objectives and Questions

Based on the proactive behavior generation framework it is described in chapter 4, this study aims to present how *the creative behavior of the robot* is perceived, which is achieved through proactivity during human-robot interactive task scenario. As creativity is seen as bringing novelty, we hypothesize that such behavior will be appreciated by the human users. At the same time since proactivity is aimed to take initiatives, we hypothesize that proactive behavior during a task will be seen helpful as well by the users.

Therefore, we came up with the following hypotheses about users' perception during Human-Robot Interaction setting, where the user is also supposed to perform a task and the robot is proactively interacting with the users:

**H1:** The users will appreciate interactions initiated by the robot even during the tasks for which the participation of robot is not necessarily needed.

**H2:** Users will find robot's initiatives in interaction helpful for achieving the task.

### 6.2 System Design

#### 6.2.1 Task and Phases

A common home scenario task is used: cooking recipe. Seven recipes from different cultures, about which the participants are not familiar with, are selected. A list of all the ingredients of the recipes is given and the users were asked to memorize each recipe and the ingredients. During experiment, a Pepper humanoid robot (Pandey and Gelin, 2018) was interacting with the user. The experiment consisted of two phases:

- **Phase 1:** A list of all the ingredients is shown and the user is required to select the ingredients of a particular dish.
- **Phase 2:** User is asked to first recall the name of a dish and then select the ingredients of that dish from the list.

#### 6.2.2 Types of proactive interactions

Interaction strategy is focused on highlighting the proactivity of the robot. For this a set of "helpful" interaction is instantiated as the proactive behaviors of robot:

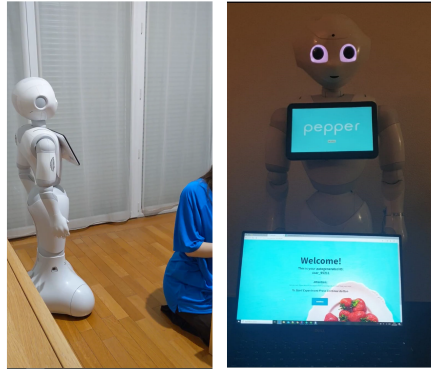


FIGURE 6.1: **Various Experimental set up** Robot behind (left) and in front of user (right).

1. Suggestive interaction: Proactively suggesting an action to the user, when the user is either not acting (i.e. became silent) for a long time or started to take repetitive wrong actions.
2. Corrective interaction: Proactively correcting an action of the user, when user makes mistakes, such as selecting wrong ingredients to reach targeted goal.

## 6.3 Method

In this study, we try to explore the perception of users on the usefulness of a robot, which is creatively engaging itself in a task performed by the user. In this regard, proactive actions of the robot are instantiated, with the aim to help the users, for those tasks in which robot's intervention is not necessary. Hence the robot is simply trying to be creative there. Then the users' feedback are collected and analyzed along various dimensions. The study conducted during Covid-19 lock-downs. Regarding to the restrictions, methodology of the study updated couple of times to match with the needs of diverse environments.

### 6.3.1 Study Design and Setting

#### 6.3.1.1 Setup

The experiment were conducted at the participants own houses in Paris, France. An Human-Robot Interaction scenario was initialized in each experimental setup, which were different locations. Typically an user was facing a computer screen and robot was placed in a location, so that it can see both user and screen and exhibit its proactive behavior. This setup aims to give an impression of robot watching user and give its opinion to the latest change at the environment. However, due to the circumstances, the experiment had to be conducted at user's own home without attendance of a conductor. Therefore the relative spatial setup of the experiments were varying according to participants' preferences. Some of the setups are presented in Figure 6.1.

### 6.3.2 Participants

A total 11 participants (3 Female and 8 Male, average age 27.73 , std 1.84) were used in the study. They had STEM backgrounds and their familiarity with robots was high.

Experiment was conducted in English. None of them are native English speaker but all of them are fluent in English. All participants signed consent form before they start and answered post-evaluation questionnaire. The quick interview was hold with each participants, they share their thoughts about the experiment after completing it.

### 6.3.3 Measures

Our evaluation metric is qualitative observations and self-report questionnaire. The questions of questionnaire were combined from ALMERE questionnaire (Heerink et al., 2010) which is assessing of acceptance of social robots and specific questions for assessing proactivity.

### 6.3.4 Procedure

Procedures are given to the participants via email. The email divided into different parts to explain setup robot application, explaining the task and consent form. After setting up the experiment and signing the consent form. It is told that they play a Recipe Game where they select ingredients for given recipes. The game has 2 phase; First Phase; a recipe assigned to them and it is expected to select ingredients of it. Second Phase; they compose another recipe by selecting it's ingredients from the left container. The Pepper robot is provided with the information on set of actions needed for a selected recipe. The robot follows the actions of the participants from a web-based interface.

### 6.3.5 Ethical Consideration

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The participants were SoftBank Robotics Europe employees and provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article

## 6.4 Results and Discussions

In this section, we will provide preliminary analysis of the user's perception on the proactive behaviors of the robot. In the current discussion, we will focus on users' feedback they gave after finalizing task.

The result of mean value analysis of post-evaluation questionnaire is presented in figure 6.2.

It is interesting to observe that the robot's behaviors are perceived as proactive actions in majority of cases, therefore, validating the objectives behind designing such behaviors. The robot is perceived as adaptive and at the same time the behavior is enjoyed, hence the creativity part seems to be experienced by the user. Also such behaviors are seen as trustworthy. Therefore, the hypothesis **H1** (*i.e. the users will appreciate interactions initiated by the robot even during the tasks for which the participation of robot is not necessarily needed.*) is supported positively.

Also users have found various advice given by the robot as helpful in achieving the goal. Therefore, hypothesis **H2** (*i.e. users will find robot's initiatives in interaction helpful for achieving the task.* ) is also supported by such preliminary studies.

Nevertheless, there have been some other factors on which uses have shown disagreements such as the perceived usefulness and sociability of the robot. Further

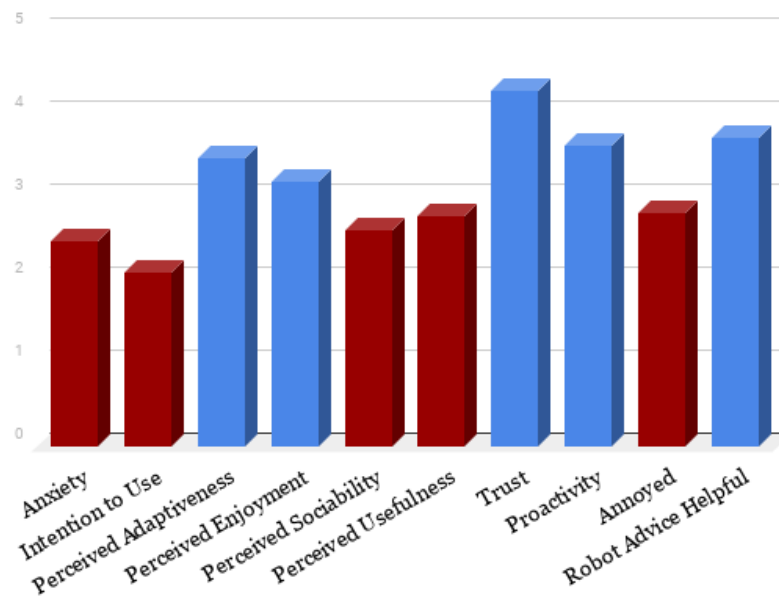


FIGURE 6.2: **Results of post-evaluation questionnaire;** Mean value analysis of ALMERE questionnaire and other questions listed in X axis. Y axis represents the 5 point Likert scale from 1 - Disagreement to 5 - Agreement. Agreed factors showed with blue block and disagreed factors showed red block.

investigation on these aspects will be done. Detailed analysis and discussion on such aspects are beyond the scope of the hypothesis studied in this paper, which are centered around proactivity and creativity.

However, we also want to provide a glimpse of some feedback we received around some of these aspects. Some participants found it distracting when the robot is speaking or explaining verbally while at the same time there is instruction or text on the screen as well. Especially, when robot tried to explain what user needed to do in each page. Users stated that they prefer they read it through the screen, instead of robot talking at the same time. Such confusions by the simultaneous multi-modality of robot's behaviors, causing distraction, might be one of the reasons that although the robot's advice was seen useful, the perceived usefulness of it was not seen as equally high.

This points towards more detailed investigation for developing the right modality of exhibiting the proactive behavior.

Also there were a set of explicit questions related to the second phase of the study, as shown in Table 6.1, to understand the intuitiveness of the experimental tasks and the flow. And to explore if robot is seen useful in confusing situations.

Only 33% of the participants understood instructions and remember one recipe which was the first recipe in the list. Almost half of the participants did not even understand what they need to do in phase 2. As a result of that, participants were led by the robot. They stated that especially in phase 2, they let robot to lead them. User's are happy that robot is helping about their choice. Some comments from the users:

- "I knew that robot is going to help me, so I select one random ingredients look like its mostly used in recipes and let robot guide me"

TABLE 6.1: Questions Specific to the 2nd Phase of Experiment

Personal Questions		
	YES	NO
Do you select a recipe when started 2nd Phase?	3	8
Do you understand what to do on 2nd Phase?	6	5
Perception Questions		
	MEAN	
Trying to help me	4.454	
Consider my needs	2.818	

- *"When I couldn't find out the ingredients robot recommend me, I waited a little bit because I knew that robot tell me again"*

Approximately 27% of the participants recall the recipe and try to follow it. 72% of the participants start by selecting a random ingredients and follow a robot's suggestions. In total 90% of the participants stated that they know if they select one ingredients robot would help them to finalize the recipe. Only 10% of participants fail to select any recipe in phase 2, and they stated as a reason that robot's help was dominating and became annoying. So, they terminated the experiment there.

We assume that even user failed to remember the recipe or understand the task in phase 2, interaction with robot lead them to select ingredients. Since, participants do not know the capability of robot, they could have been creative and tried to teach robot a new recipe. However, participants choose to let robot lead and follow robot's suggestion.

## 6.5 Conclusion

This study is an attempt to explore the behavioural aspect of creativity in robots, in the context of Human-Robot Interaction. We hypothesized the dimension of bringing novelty (to be creative) in behavior by proactive actions, by letting the robot to initiate a suggestive interaction for a task which human is supposed to do. We have presented experiment and analysis with real robot. The preliminary finding is supporting the hypotheses of enjoyment and helpfulness of such behaviors.

Other future work includes exploring the relation between the task and the need the creativity. Further, it will be interesting to explore the learning aspect of Human-Robot Interaction for elevating the creativity of the robot.





## Chapter 7

# Creative Recipe Task

The study in this section is published in the special issue of Creativity and Robotics in Frontiers Robotics and AI Journal.

### 7.1 Research Objectives and Questions

It is aimed to study how the robot's creativity (which is instantiated through the proactive interaction) affects i) the perceived creativity of the robot and ii) the creative process of the human during an HRI task scenario. Recall that creativity is seen as bringing novelty, and proactivity is anticipatory behavior aiming to help in the task. Therefore, we developed the following hypotheses to study their relation and effects on the user's perception.

**H1: Proactivity and Perceived Creativity of the robot;** The proactivity of the robot behavior will affect the perceived creativity. Proactivity in the robot behavior and its perceived creativity are related.

**H2: Proactivity and the User's creativity;** There exists a link between the robot's proactivity and the resulting creativity in the user (measured by the novelty of the products that the user creates in the HRI task). That is, proactivity of the robot and the facilitated creativity in the user are potentially related.

**H3: Proactivity and Goal Achievement;** There is a relationship between the robot's proactivity and the success of the HRI task. That is, the proactive behavior of the robot can help to achieve the goal of the task.

**H4: Proactivity Level and User Perception;** Different levels of proactivity of the robot will have different user experiences on the perceived attributes, including perceived and facilitated creativity.

### 7.2 System Design

#### 7.2.1 Design Overview

This study explores the behavioral aspect of creativity during HRI using a robot as a proactive agent, creatively engaging in a task performed by the user and generating suggestions as communicative behavior to guide the user while achieving their intended goal. In this regard, *proactive behavior* of the robot is defined as instantiating behavior for suggesting the users, where the robot's intervention is not necessary or not requested by the user. We have considered a common home scenario task - cooking a recipe - that is explained below.

### 7.2.2 Task Definition

We have chosen a task in which the user could be creative and would not necessarily need the robot's help to complete the given assignment. Generating cooking recipes can be seen as a creative task, in which the users could converge towards different recipes by using a similar set of ingredients.

Most likely, users have different knowledge about the typical recipe. That is why users were provided with seven recipes with the dish's name and ingredients to set the expected ground for the cooking recipe scenario. Each dish has six different ingredients. The recipes are different. However, each dish shares one or more ingredients with other dishes. In total, twenty-two ingredients were given in alphabetic order from different categories: **Proteins**; chicken, foie-gras, ham, lardon, **Vegetables**; garlic, pumpkin, spinach, truffle, onion, pepper, nutmeg, **Dairy products**; milk, cheese, butter, eggs, **Processed stuff**; bread, barbecue sauce, stock, wine, **Sugary stuff**; sugar, honey, **Basics**; flour. Typical French recipes such as quiches, soups, toasts were chosen to eliminate the hassle of learning new recipes. The whole task is divided into two phases to first study the effect of proactive behavior for a predefined recipe and then give the user a chance to be creative by eliminating the predefined recipe. With each user, the experiment starts with **Phase 1**, and continues with **Phase 2**.

**Phase 1:** A dish is assigned to the user. The participant should select the exact ingredients for the given recipe. Thus, the participant and the robot both know, which recipe is targeted.

**Phase 2:** The user is asked to create a dish by using the given ingredients. The robot does not know about the target dish.

### 7.2.3 Design of the Proactive Behavior

In this study, the proactive behavior of the robot uses shared principles of creativity and proactivity. Those principles consist of (i) being anticipatory: based on a particular state, (ii) self-initiated, as producing proactive suggestions without explicitly demanded by the user, and (iii) future-driven, as trying to converge towards the needs of the goal. Based on this; rule-based proactive behavior generation framework (described in ??) is adapted for the robot to instantiate verbal suggestions depending on the user's task. Rules are selected based on the task's needs and the understanding of intention recognition. With the help of the rules, reasoning occurs to instantiate the parameters of the proactive suggestions. The robot's knowledge and this reasoning result are proactive robot communication (see Figure 7.2). The decision flow of instantiating the proactive robot communication (aka proactive suggestion) is shown in Figure 7.1.

The set of rules varies according to the need of the task. The tone of the proactive behavior slightly differs depending upon whether there is a target dish assigned by the system (Phase 1) or not (Phase 2). The decision-making processes to instantiate the proactive interaction, for Phase 1 and Phase 2, are shown in Figure 7.1-A and Figure 7.1-B, respectively.

In both cases, instantiating the proactive communicative robot behavior starts with intention recognition of the user actions. Intention recognition is the recognition of the user's target dish by interpreting the robot's knowledge of the dishes and the ingredients that the user has selected so far. The ingredients that the user selects indicate the their commitment to the dish they want to achieve in the future, which is tagged as the user's intention. The recognition process is a simple rule-based mechanism that checks how close the user is to achieve one goal. The user's intention

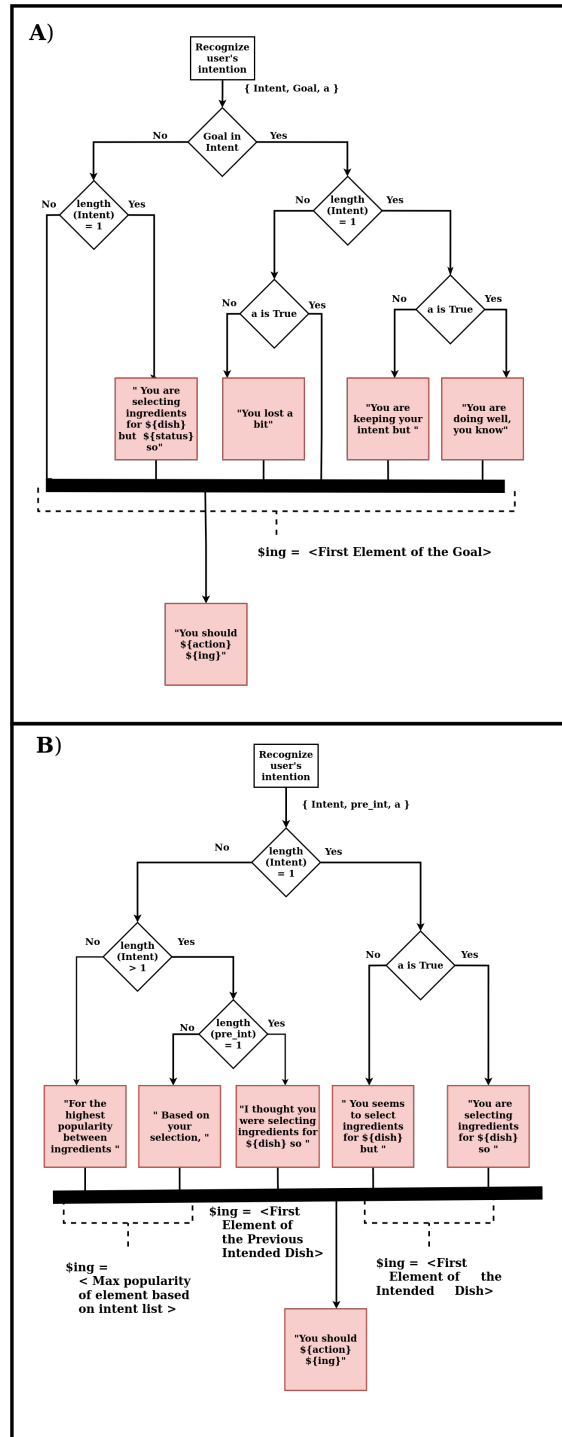


FIGURE 7.1: **Diagram of Proactive Robot Communicative**, is showing how proactive suggestions is initiated. It is starting with recognizing user's intention. The list of user's intent passes to the reasoning mechanism which is based on layers of rules. Red boxes shows the robot response. In boxes, the template is given to create a sentences. Between curly brackets of  $\{...\}$  filled with symbolic representation of action ( $\{action\}$ ), object – ingredient ( $\{ing\}$ ) or dish ( $\{dish\}$ ) – or the result of system ( $\{status\}$ ). Each boxes concatenates to each other on the road to create proactive behavior of the robot.

is based on the least number of ingredients left from the set of known dishes. The intention is either the list of dishes or a single dish, depending on the situation of the selected ingredients so far. The user is also free to move away from the set of dishes that the robot knows and create their own dish by selecting a new list of ingredients.

The user is assumed to be reliable and collecting ingredients to complete a dish. The user willingly performing a faulty behavior to deviate the intention recognition is not handled in this recognition mechanism. In the beginning, the intention of the user is all the dishes that the robot knows. Then, the recognition mechanism updates the user's intention for every change in the state (adding or removing an ingredient). Respectively, the system initiates the new proactive suggestion.

Different sets of rules are used to instantiate the sentences' templates, depending on whether the goal is assigned (phase1) or not (phase 2).

In phase 1 (see Figure 7.1-A), it is crucial to accomplish the assigned dish by selecting the exact ingredients of the target dish. That is why intention recognition responds to each change in the state by updating the list of intentions. Updating the intentions triggers the process of instantiating the sentences' templates. The next step of '*Goal in Intent*' (as shown in the Figure 7.1-A) is to check if the targeted dish (which is the Goal as shown in the Figure 7.1-A) is part of the intention list or not. This reasoning gives the impression that the user is on the right track. Then, the length of the intention list is checked to elaborate more on whether the user follows one specific dish or there are still multiple possibilities. For the cases in which the goal is in the intention list, the robot gives feedback type of suggestions that gives the information about the status of the action. The action represents the selected ingredient and is denoted by  $\langle a \rangle$ . The action status could be *True* or *False* depending on whether the played action complies with the goal's recipe. For example, say *Fois Gras Toast* is assigned as a target dish, the user has already collected *foie-gras* and *truffle*. The recognized intention is *Fois Gras Toast*. Now the user collects *butter*: this action is *False* because collecting *butter* does not comply with *Fois Gras Toast*'s recipe since the recipe does not include butter. Therefore, the instantiated interaction will look like, '*You lost a bit. You should remove butter.*'. Here it is interesting to note that such feedback was not requested by the user. Therefore, from the user's perspective, it is a proactive action, as the robot is acting by itself by anticipating the future situation.

In phase 2, (see Figure 7.1-B) it is crucial to keep up with the user to assist the user in accomplishing the user's goal. The difference from the phase 1 is that the robot is unaware of the goal: the user chooses it. The robot uses intent recognition to predict the goal of the user. The rules of the proactive suggestion focus more on the user's consistency than on assisting. That is why the current intention list (which is the *intent* as shown in the Figure 7.1-B) and the previous intention list (which is the *pre;nt* as shown in the Figure 7.1-B) are used for reasoning. After updating the intention list, it is checked that whether or not the user's intention is a specific dish. This means the length of the intention list is equal to one, therefore, a single intent is recognized. This case is treated in the similar way as a supposedly target goal. That is why the status of the action is checked, as explained for the similar situation of Phase 1. If there is no specific intent, the system tries to lead the user by suggestions. The reasoning about suggestions starts with checking if there is any intent in the intention list or not. If the length of the intention list is equal to zero, the system tries to lead the user by suggesting the most frequent ingredient. If there is an intention which means the length of the intention list is non-zero. Then, the length of previous intent is checked to be equal one to determine if the user had a goal. In that case, suggestion instantiates for explaining its reasoning and objectives of the previous goal. For example, in this situation, the robot said '*I thought you were*

*selecting ingredients for Foie Gras Toast so you should select truffle.*" Otherwise, the suggestion relates to the most popular element in the list.

## 7.2.4 Implementation Details

The Pepper humanoid robot interacted with the participants during the experiment. The robot followed the actions of the participants from a web-based interface and instantiated interactions from the Android application of the robot. The task was presented on the laptop with a web-based interface. The participant can only take actions and decisions with the laptop. The graphical user interface (GUI) that the participants faced is shown in Figure 7.4. The connection between the robot application and the web application is made with a Firebase database (Moroney and Moroney, 2017).

The interaction flow is shown in Figure 7.2. The diagram shows the combination of web-based task flow, the robot interruptions and the participant's actions. The task and behavior system are separated from each other to divert the participants focus from the robot to the task.

## 7.3 Method

### 7.3.1 Study Design and Setting

#### 7.3.1.1 Study Design

A between subjects study was conducted with one independent variable; the proactive behavior of the robot, which has three conditions *high*, *medium*, and *no proactive*. The different conditions of proactive behavior aim to change the frequency of exhibiting proactive interactions. In full proactive conditions, it is expected that the robot will provide feedback after each action of the user. On the other hand, in no proactive condition, the robot is not providing any feedback. And an intermediate condition (medium proactivity) is detailed below, along with details of the other conditions. The robot also talks at the start and between each phases of the task. Participants were randomly assigned to different conditions.

#### 7.3.1.2 Conditions

The robot followed the general flow of the interaction with the participant, as shown in Figure 7.2. The main aim of the added interactive behavior is to balance the frequency of the robot's talk between different conditions. In a between-subject study, the participants only interacted with one of the conditions. Three different conditions of robot's interactive behaviors are instantiated for this experiment. These conditions are:

**Condition 1: No Proactive Behavior,** The robot does not provide any explicit or implicit directions to the user in terms of the status of the action. After each step of the ingredients selection process, the robot simply utters "oh"<sup>1</sup> is used as a neutral token to acknowledge to the user that their action has occurred.

<sup>1</sup>In the implementation using a Pepper robot, the exact token used was "oo", as "oh" sounded unnatural given Pepper's text-to-speech component. We choose "oh" because it is a "knowledge state marker", that is, when "oh" is uttered by the robot, it informs the user that the action they have undertaken is understood by the robot, but does not give (neither positive nor negative) feedback on this action. Thus the as a knowledge state marker (as described in Heritage (1984)), "oh"

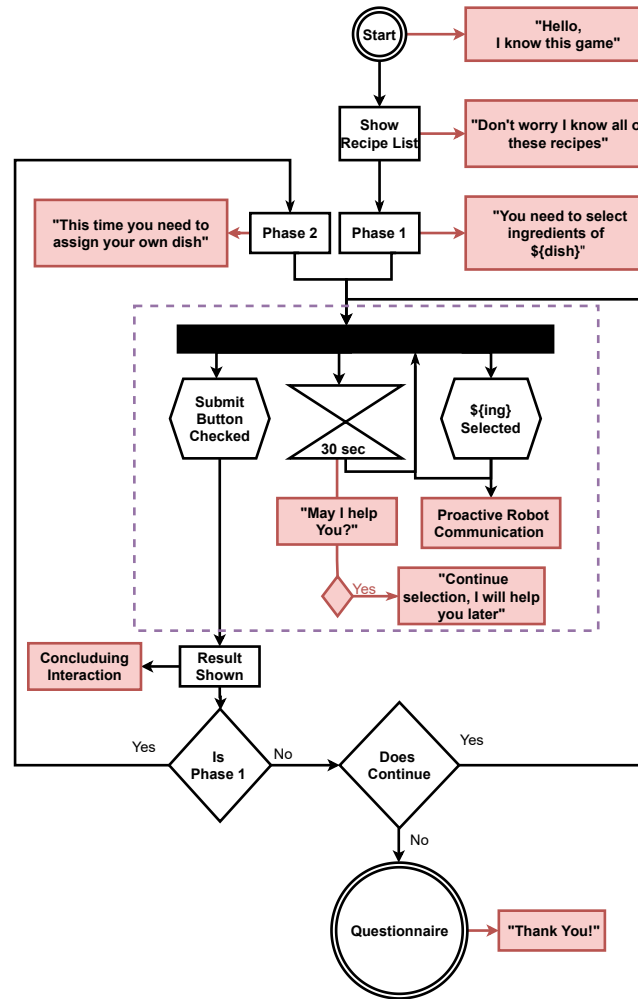


FIGURE 7.2: **Activity Diagram of Interaction Flow** indicates the actions of the task, the robot and the user. Black rectangle boxes represents the pages of the task and diamond boxes shows the decisions of the task for general flow of phases. Robot responses is indicated with red boxes. Red boxes with black arrows represents the sentence will be created. The user's actions represented with hexagon boxes.

**Condition 2: Medium Proactive Behavior,** In this condition of experiment, the robot provides communicative proactive action at every third action of the participants, and utters "oh" in other steps. The frequency of interventions is decided based on the approximate number of actions played in each phase. If everything goes well, the participants need to play six action to accomplish the goal. It is decided that the robot acts at least every third action to (at minimum) have support at the half of each phase. The proactive actions are instantiated through a response trigger mechanism described in the section 7.2.3.

**Condition 3: High Level (Full) Proactive Behavior,** In this condition, the robot instantiates and provides communicative proactive action after each action of the participants.

Thus, the kind of information the robot provides in medium and high proactive conditions is related to the ingredients selected by the user for a dish. At the end of each phase of the task, which is supposed to result into a recipe, the robot provides a summary of the selections. The response of the robot is instantiated by a matching

mechanism using the database of known recipes, their ingredients, and the selection of ingredients by the user. If participant created a new recipe (mainly by selecting a novel set of ingredients) that the robot could not find a matching recipe, robot asked the name of the potentially "new" recipe of selected ingredients, to use this information for interaction purpose.

### 7.3.1.3 Setup

The experiment was conducted at the various meeting rooms of SoftBank Robotics Europe. The experimental setup is shown in Figure 7.3. The participant sat in front of a laptop to get engaged in the task. A Pepper robot was placed relatively left or right of the user. Participants manipulate task environment on the screen of the laptop through mouse or track pad. Self-report questionnaire is attached to the task, automatically pops up, once the task is over. As a part of COVID 19 guidelines, all equipment was sanitized before and after each session. Participants were left alone in the room with the robot during the study.



FIGURE 7.3: The set up of experiment. Participant sit in front of a laptop and robot placed next to user. They share the space as the robot is looking at the screen over the participants.

## 7.3.2 Participants

A total of 30 participants ( 11 female and 19 male, average age 32.23, standard deviation 6.76) participated in this experiment. All of them were employees of SoftBank Robotics Europe, Paris. They had some experience with the Pepper robot. However, they had different backgrounds: technical (hardware, software) and non-technical (marketing, communication, welcome desk). The participants were also fluent in the language of the experiment: English. All participants gave their consent and signed the form to use and share their anonymous data for scientific purposes.

## 7.3.3 Measures

Different evaluation metrics are used to investigate different aspects proactivity and creativity. Our measures are divided into three sections to assess the following:

*Creativity of the user*; to define and evaluate the participants' creativity, metrics were inspired by divergent thinking. Thus, the creative thinking of the user often



links with divergent thinking tests. Traditional methods of scoring divergent thinking (i.e., fluency, originality, and flexibility) are the most used methods for assessing the potential of creativity (Runco, 1992). In this study, we created an assessment influenced by the Torrance Test of Creative Thinking (Torrance, 1974) by focusing on fluency in the task - *How many dishes were achieved?* - and originality - *How many new dishes were created?* - . These two scores are used to measure the creative thinking of the user. The total number dish summed at the end of each task. It included phases 1, 2 and repetitions of phase 2. The number of new dishes is the count of all dishes created in phase 2 and repetitions of phase 2. Dishes in the list of ingredients have the same recipe with dishes in the recipe list are extracted.

*Creativity of the Robot*; to assess some creative aspects of the robot's behavior, a different self-report questionnaire was used to assess the participants' perception of the robot. The questionnaire is a combination of different sections to assess demographic information, participants personality and creativity using a Likert Scale, acceptance of social robots from the ALMERE questionnaire (Heerink et al., 2010), comprehensive impression of user experience from User Experience Questionnaire (UEQ) (Schrepp and Thomaschewski, 2019) and some specific questions directly related to engagement, proactivity, task and overall interaction. In this paper, we did not include all the scales from the questionnaire, such as ALMERE and UEQ. Instead, we included the scales that could be applicable to the defined situation such as perceived adaptivity, perceived enjoyment, attitude, perceived usefulness, trust and dependability. The scales assess the participants perception about the robot's creativity on generating proactive actions that are task-oriented.

*Effect of Proactivity*; to assess the effects of different conditions of proactive behavior on the task, we check the success rate of phase 1. In phase 1, a random dish is assigned to the participants, and it is expected from the participants to select the exact ingredients which were shown earlier to them. We also analyzed the time that they spent during the selection process in phase 1. The spent time is calculated by the time passed that the user started to select ingredients until they submitted their selection by clicking the submit button.

### 7.3.4 Procedure

Procedures for all conditions are identical except the robot's interruption frequency during the execution of the phases of the task. After signing the informed consent form, participants are informed about the experiment. Participants were given the choice of suggesting as many recipes as they wished for the upcoming hypothetical company event. The way to suggest is by using the online platform. They were informed that the online tool would guide them on how to proceed. Sample recipes were given to remind them how ingredients may be used. They could list as many recipes as they wanted while the *Pepper* robot accompanies them. They were reminded to be aware of the existence of the *Pepper* robot. Then, the experimenter left the room. Each participant interacted with one condition of the proactive robot behavior (condition 1: no proactive, condition 2: medium proactive, condition 3: high proactive), was assigned randomly, and maintained during both the phases of the task. As a result, each participant can generally work on two kinds of dishes: one that it is assigned to them and one that they created. Participants were also allowed to proceed without selecting any ingredient by submitting the result without collecting any ingredients at the execution of the phases in page (in Figure 7.4 - D). The proactive robot behavior is initiated depending on the robot's knowledge. In this experiment, task space and the participant's action in the task space were used to

enrich the knowledge of the robot. The robot stayed ignorant of the other possible actions from the participant or the shared environment. After each participant had completed the task, the self-report questionnaire was submitted. The self-report questionnaire is attached to the task interface. It automatically pops up when the task has been completed. After the participants completed the task and the self-report questionnaire, the experimenter back to the room for a small interview.

### 7.3.5 Ethical Consideration

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The participants were SoftBank Robotics Europe employees and provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

## 7.4 Results and Discussions

This section presented an evaluation for our four hypotheses (outlined in section 7.1). We take the user study from 30 participants, 10 for each condition (no, medium and high proactive behavior of the robot). We conducted a one-way analysis of variance (ANOVA) in each of our hypothesis, to see if they are different for the three conditions: no ( $n = 10$ ), medium ( $n = 10$ ) and high ( $n = 10$ ) proactive behavior with a post-hoc (t-test) to compare differences in paired conditions. To test our hypotheses, recall that we use a combination of qualitative and quantitative measures (as is further illustrated in the following sections). For the qualitative data, we analyze the results of the questionnaire as the post test given to the participants. For quantitative data, we use the meta data generated from the results of the task (such as the number of times a dish was created). The data is presented as the mean and the standard deviation.

Before conducting the ANOVA test, we check that the following assumptions are not violated: i) no significant outliers, ii) test for normality (by Shapiro-Wilk's test), and iii) homogeneity of variances<sup>2</sup> (by Levene's test). We do not check for the independence of observations, as each participant belongs only to one condition/group. For the test to detect outliers, we check outliers for our quantitative data collected but we keep the data since we manage figure out the reason of the outlier. That is discussed in following section. However, the qualitative data outliers are subjective reports and are essential for our analyses (for e.g. how was the perceived adaptivity of the robot). However, we do report this range of differences in the user's opinion. The results are shown according to each hypothesis in the following sections. The significance of  $p$  is denoted by stars \* from high impact (\*\*\*)  $p < 0.001$  to low impact (\*  $p < 0.05$ ) and non significance denotes by (ns  $p > 0.05$ ). Qualitative observations are discussed in the following section, along with various attributes and pointers for further investigation.

### 7.4.1 Proactivity and Creativity

The *Novelty* scales of UEQ (User Experience Questionnaire) measures how much the design of the robot's behavior is perceived as creative. The user is asked to

<sup>2</sup>based on the practices as outlined in this resource <https://www.datanovia.com/en/lessons/anova-in-r/#check-assumptions>

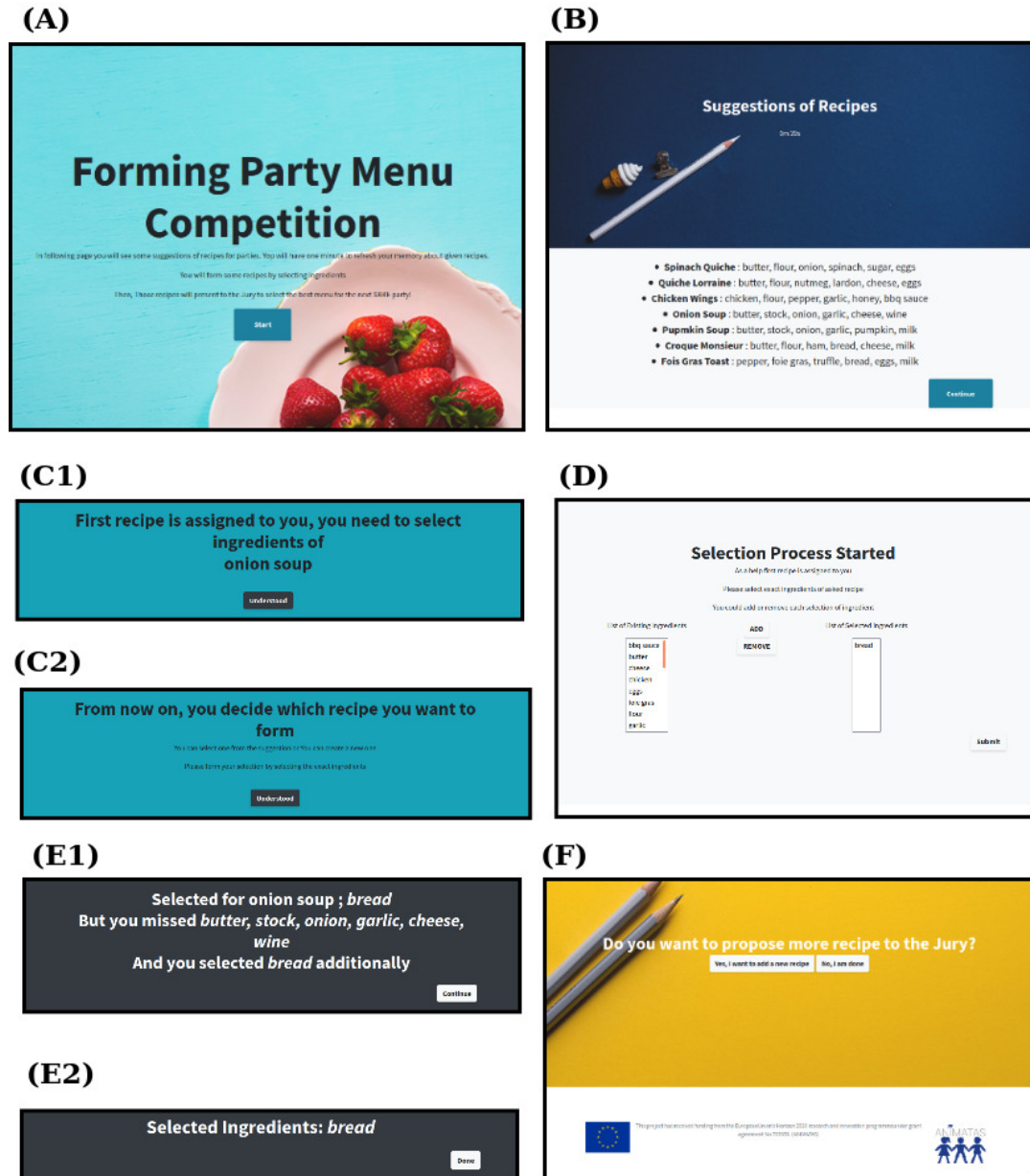


FIGURE 7.4: GUI of Cooking Recipe Task; Diagram combines the pages of the web-based task application. After the robot connected - Additional pages omitted -, (A) is welcomed the user and explain about the aim of the task. (B) is only visible for 1 minute, and it presents the examples of recipe. (C) is changed according to phases of the task, (C1) is the phase 1, where a dish assigned and (C2) is the phase 2 where the participant has a free of choice. (D) is the page that phases of task occurs, where the robot proactive behavior is activated. It is identical for all phases. (E) is the result pages after the each selection process. (E1) has a specialized view for the phase 1 which provides more information. (E2) is the result page for phase 2 which only shows the recent information of selection. (F) is the page comes after phase 2 and let the participants to continue to create more dish or finalize the task.

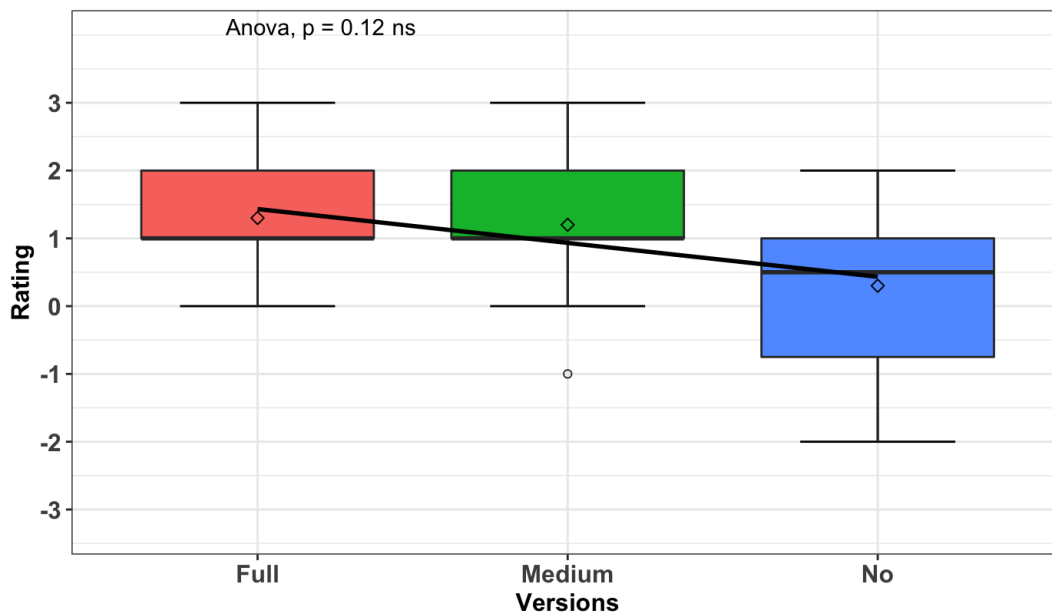


FIGURE 7.5: **Analysis result of Novelty from UEQ**; The graph scaled on positive as creative and negative as dull. It shows that in each version of proactive behavior, the robot rated as creative, however, there is a visible difference on the mean from full to no proactive behavior.

rate from dull to creative, with statement “*In my opinion, the idea behind the robot’s behavior and design is –*” on a 7-point scale (-3: dull to 3: creative). We conduct a one-way ANOVA test to see if the perceived creativity of the robot was different in our 3 group conditions. We run tests before conducting the one-way ANOVA test on the dependent variable (creativity) to check that the assumptions are met. We only have one outlier which is not extreme; one user in the medium condition rated the perceived creativity of the robot as dull (-1) compared to the  $MEAN = 1.2$  of the group. The variable was normally distributed ( $p > 0.05$ ) for each group, as assessed by Shapiro-Wilk’s test of normality. We can assume the homogeneity of variances in the different proactive conditions ( $p > 0.05$  by Levene’s test).

The results of the one-way ANOVA test on perceived creativity of the robot and our 3 conditions are given as ( $ns$ ),  $F(2,27) = 2.28$ ,  $p = 0.12$ ,  $ges = 0.14$ , as presented in Figure 7.5 (where  $F$  is the results of the test, and  $ges$  is the generalized effect size). Given the value of  $p$ , we cannot conclude on the difference between the group conditions and the perceived creativity of the robot. As shown in the figure, the mean and standard deviation (SD) of the conditions are the following: high proactive condition with  $MEAN = 1.3$ ,  $SD = 0.90$ , medium proactive condition with  $MEAN = 1.2$ ,  $SD = 1.08$ , and no proactive condition with  $MEAN = 0.3$ ,  $SD = 1.27$ . What is interesting to see is that the means of all three conditions of the robot’s proactive behavior are perceived as creative (with values above 0 in the UEQ). The two levels of proactivity (medium-high) are perceived as more creative ( $MEAN = 1.2$  and  $MEAN = 1.3$ ) respectively than the no proactive condition ( $MEAN = 0.3$ ). In the case of the no proactive condition, the mean is close to zero with  $MEAN = 0.3$ ,  $SD = 1.27$ , suggesting that participants may not have been able to assign a clear verdict about creativity in the robot’s behavior. This shows that there

is some perceivable difference to the user between the no proactive conditions and the proactive conditions, though not statistically significant according to the method used. Looking deeper into the generalized effect size, we see that  $ges = 0.14$  (14%). This means that 14% of the change in the perceived creativity of the robot could be affected by the proactive conditions.

Thus even without a statistically significant difference (according to this method), as part of an exploratory analysis we looked at the means of each conditions and effect size, and found that there still could be links with the proactivity of the robot and the perceived creativity of the robot. It is plausible that the users hesitated to rate the robot's creativity as dull to not seem harsh, given the positively skewed labels. During the post-experiment interviews, the participants indicated that the simple acknowledgment from the robot (the knowledge state marker - "oh" - ) was seen as better than no acknowledgment at all. For future work, it may be better to consider no verbal feedback whatsoever from the robot to test no proactivity.

Additionally, we did not find a statistically significant difference between the two levels of proactivity according to this method (medium with  $MEAN=1.2$ ,  $SD=1.08$  and full with  $MEAN=1.3$ ,  $SD=0.90$ ). Therefore, it is too early to establish any relationship between the frequency of proactive behavior and the scale of perceived creativity in the behavior. Therefore, H1 is not completely supported, in the sense the both parts are not validated: **(H1: Proactivity and Perceived Creativity of the robot;** The proactivity of the robot behavior will affect the perceived creativity. Proactivity in the robot behavior and its perceived creativity are related). The exploratory results suggest that proactive condition is affecting the perceived creativity of the robot. But we could not find statically significant links between the perceived creativity of the robot and the proactive conditions robots to establish any relation. That is why there is a need of further investigation in this direction.

## 7.4.2 Observed Creativity in the User

To further explore the factors associated with the user's creativity, we conducted various analyses on the quantitative data from the study, such as: how many recipes were completed successfully?, How many new recipes were created?

The design of the experiment was to encourage participants to complete at least one dish in phase 1 and then to complete or create at least one dish in phase 2. After that, participants were free to continue further iterations of phase 2 and complete or create more dishes. Participants can also skip a phase without completing or creating a dish.

We conduct a one-way ANOVA test to see if the total number of dishes that user completed was different in our 3 group conditions. We run tests before conducting the one-way ANOVA test on the dependent variable (total number of completed dishes) to check that the assumptions are met. We have three outliers which are extreme; three user in the full condition completed (2,5,2) dishes compared to the  $MEAN = 3.0$  of the group. The variable was normally distributed ( $p > 0.05$ ) for medium and no proactive group condition but was not normally distributed ( $p < 0.05$ ) for full proactive group condition, as assessed by Shapiro-Wilk's test of normality. We can assume the homogeneity of variances in the different proactive conditions ( $p > 0.05$  by Levene's test). The results of the one-way ANOVA test to see if the total number of dishes that user completed was different in our 3 group conditions are given as ( $ns$ ),  $F(2,27) = 0.10$ ,  $p = 0.9$ ,  $ges = 0.007$  as presented in Figure 7.6. Given the value of  $p$ , we cannot conclude on the difference between the group conditions and the total number of dishes that user completed. As shown in the figure, an almost straight

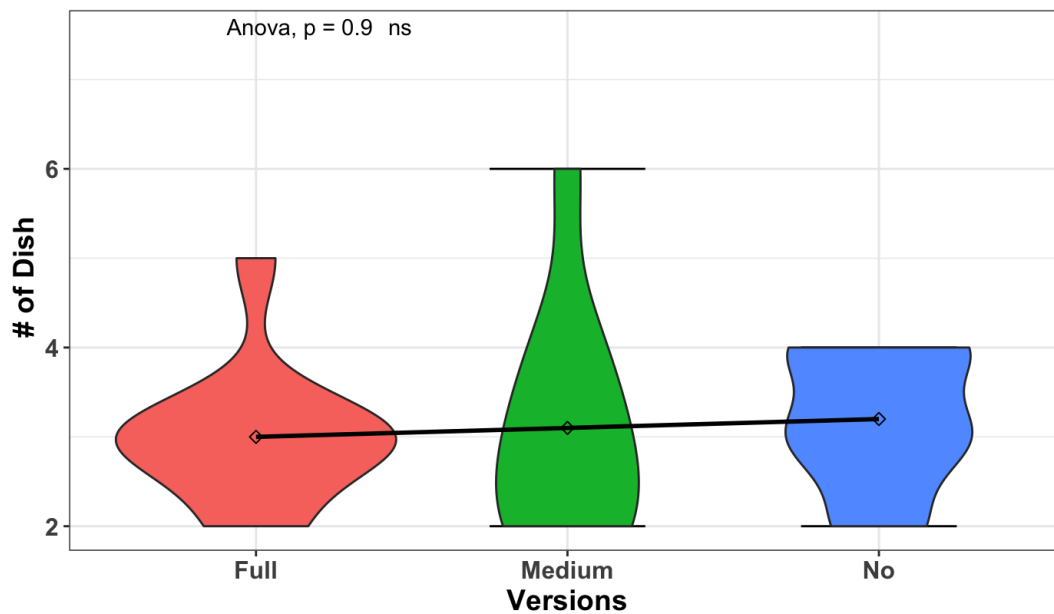


FIGURE 7.6: **Comparison Results of Total Number of Completed or Created Recipe to the Versions** Effects of different versions of robot behavior to be creative on completing or creating recipes by increasing number of recipe that is created in total is not shown as significantly changed.

trend line is observed between the conditions of the mean and standard deviation (SD) are the following: high proactive condition with  $MEAN = 3.0, SD = 0.81$ , medium proactive condition with  $MEAN = 3.1, SD = 1.28$ , and no proactive condition with  $MEAN = 3.2, SD = 0.78$ .

However, we found interesting observations when we conduct a one-way ANOVA test to see if the number of new dishes created was different in our 3 group conditions. We run tests before conducting the one-way ANOVA test on the dependent variable (number of created new dishes) to check that the assumptions are met. We have two outliers which are extreme; two user in the full condition created (1,2) new dishes compared to the  $MEAN = 0.3$  of the group. The variable was normally distributed ( $p > 0.05$ ) for medium and no proactive group condition but was not normally distributed ( $p < 0.05$ ) for full proactive group condition, as assessed by Shapiro-Wilk's test of normality. We can assume the homogeneity of variances in the different proactive conditions ( $p > 0.05$  by Levene's test). The results of the one-way ANOVA test to see if the number of new dishes created was different in our 3 group conditions are given as  $(***)$ ,  $F(2,27) = 10.62, p < 0.0003, ges = 0.44$  as shown in Figure 7.7. This graph is related to phase 2 of the experiment, where the participants were free to converge towards a dish from the list or proceed towards creating a new dish. Given the value of  $p$ , creating new dishes had a statistically significant difference between the proactive behavior conditions. We followed up by post-hoc tests (t-test) to multiple pairwise comparisons between groups. It can be seen from the Figure 7.7, there is a statistically significance difference between no proactive condition and full proactive condition with  $p = 0.000019(***)$  and between no proactive and medium proactive condition with  $p = 0.0045(**)$ . There is no statistically significant difference (according to this method) between no and medium proactive condition



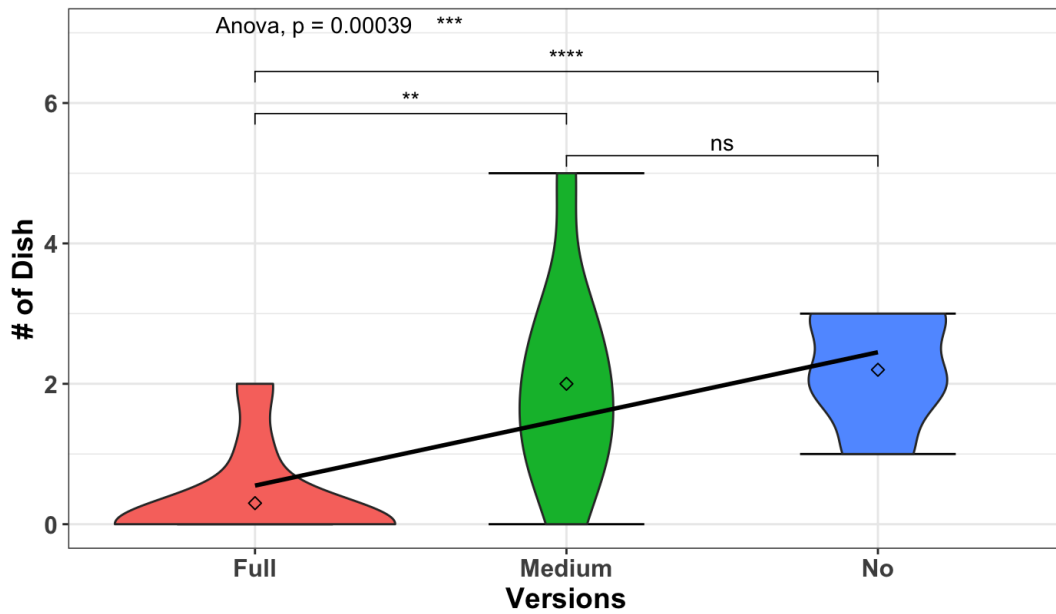


FIGURE 7.7: **Comparison Results of Creating New Recipe to the Versions** Effects of different versions of robot behavior to be creative on creating new recipes. It clearly shows that the balanced proactivity (Version of Medium Proactive Robot) is supporting more number of new recipes to be created by the users.

with  $p = 0.7(ns)$ . Thus, it is observed that the number of new dishes which is created per person is significantly lower in full proactive conditions than in no and medium proactive conditions. Even in no proactive condition with  $MEAN = 2.2, SD = 0.78$  and medium proactive condition with  $MEAN = 2, SD = 1.41$ , it shows that the number of new dishes which is created per person is lower in the medium proactive condition than no proactive condition. Hence, the analysis results support our hypothesis H2 (**H2: Proactivity and the User's creativity.**) Once the robot is very proactive and heavily interrupting the user towards achieving a goal, participants can complete the task (as shown in Figure 7.6) but are not flexible and free enough to create new recipes, as shown in Figure 7.7 hence being less creative.

Another interesting observation is that the medium proactivity condition has the maximum number of created new dishes per person (at most 5), whereas for no proactivity, most of the participants stopped after creating a maximum of 3 new dishes. In medium proactivity conditions, it is observed that the highest number of new dishes created per person. This is fascinating and suggesting a need for a balance. It hints that balanced proactivity could encourage prolonged creativity. It needs further studies to define the boundaries of the balanced proactivity.

In summary, there is no strong observation about difference frequency of proactive behavior on constructing a recipe. From figure 7.6, it is shown that the bump in full and no proactive conditions that majority of the people are tending to create three dishes. So, the proactivity has not affected their motivation of creating recipe. However, it is also observed that when there is a space between interruptions, it is a kind of encouraging the users to play more. On the other hand, when the robot proactively creates suggestions for the users, the users' creativity decreases. The users are tending to follow the robot suggestions and reducing their creativity process. As

shown in the no proactivity case, since there is no help from the robot, users tend to be creative on constructing a recipe. However, in medium and even it is shown heavily in full proactive cases, when the robot starting to help, the users' flexibility for being creative, seems to be reducing, as the users mostly go with the flow that the robot suggested. However, further study is needed to explain the reason for the changes in the user's behavior.

### 7.4.3 Goal achievement and Proactivity

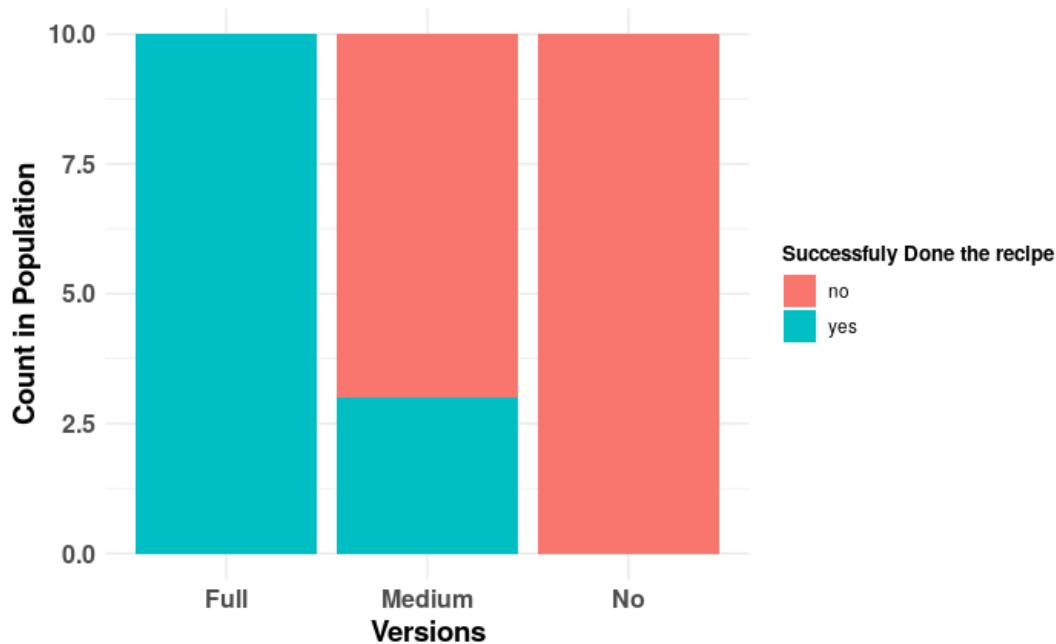


FIGURE 7.8: **Distribution of Successfully Achieving to Assigned Dish;** Graph groups the counts of number of participants who achieved the assigned goal successfully during the phase 1 to the experiment. It shows the absolute dominance of success in full proactive behavior and failure in no proactive behavior of the robot. In the medium proactive behavior of robot, variations observed to have success or failure.

To explore the benefits of proactive behavior on task accomplishment, we focus on phase 1 of the task and conducted the analyze of the comparison between each condition. How many times recipes have been done successfully? (see in Figure 7.8) and How much time does the user spend while reaching the successful result? (see in Figure 7.9) is used for analysis.

Figure 7.8 shows the successful completion of phase 1 of the experiment by the participants. As we can recall, in phase 1, the goal is assigned and the target goal is known to the robot and the user. Hence, there is a joint goal to achieve. As we can see, all the participants exposed to the full proactive robot have successfully completed phase 1, whereas all the participants of no proactive robot condition have failed. Furthermore, the failure rate was less in medium proactivity condition, which shows 30% of success and 70% of failure. Pearson's Chi Square test of independence is applied to statistically analyze the correlation between different proactive behavior conditions and successfully completing phase 1. The result shows that there is



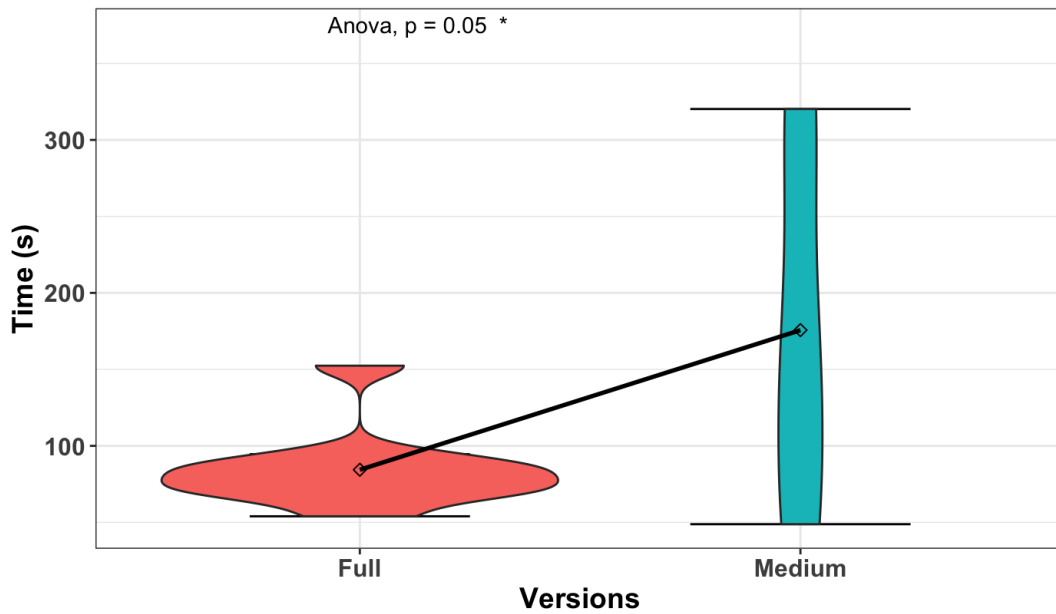


FIGURE 7.9: Detailed Analysis of Time Spend on Correct Result of Different Level of Proactive Behavior; The graphs aims to show the difference between how much time user's spend time while reaching the correct results in phase 1.

significant relation between different conditions and success,  $X^2(2, N = 30) = 21.44, p < 0.000022(* **)$  This supports our hypothesis H3 (**H3: Proactivity and Goal Achievement**; There is a relationship between the robot's proactivity and the success of the HRI task. That is, the proactive behavior of the robot can help to achieve the goal of the task.).

Further, we conduct a one-way ANOVA test to see if the time spent between participants who achieved phase 1 successfully was different in group conditions. We run tests before conducting the one-way ANOVA test on the dependent variable (time spend) to check that the assumptions are met. We only have one extreme outlier; one user in the full proactive condition spend 152 sec to reach success compared to the  $MEAN = 84.38$  of the group. The variable was normally distributed ( $p > 0.05$ ) for each (full and medium) condition. We can assume the homogeneity of the variances in different proactive conditions ( $p > 0.05$  by Levene's test). The results of the one-way ANOVA test on time spent between participants who achieved phase 1 successfully and our proactive conditions are given as  $(*)$ ,  $F(1, 11) = 4.84, p = 0.05, ges = 0.3$  as shown in Figure 7.9. Given value of  $p$ , we can observe a significant difference in time spent between participants who achieved phase 1 successfully. It should be noted that phase 1 does not include the creation of new recipes. Therefore, these two findings combined also indicate that participants are more successful and less time-consuming in reaching the goal, with robots having a higher frequency of proactive behaviors.

#### 7.4.4 Proactivity level and effects on perceived attributes

Figure 7.10 shows the overall impression of the participants about the robot's behavior in different versions. Although we did not find statistical significant differences (according to this method) to reach any conclusion or establish any solid relation for

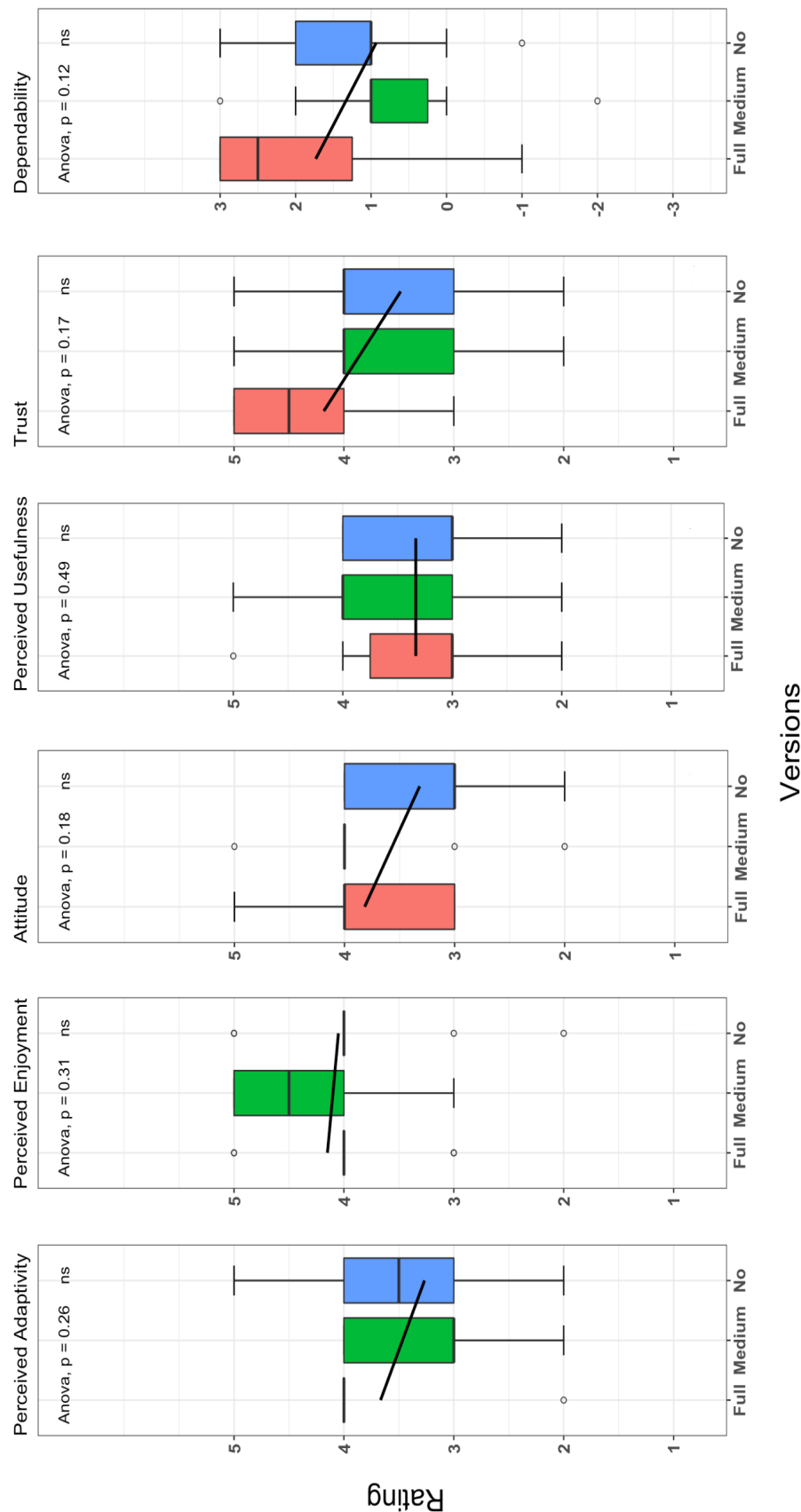


FIGURE 7.10: **Analysis of Questionnaire**; The graph visualizes the united results of questionnaire with ANOVA and post-hoc t-test analysis. The scale is 5 point likert scale [ALMERE] except for Dependability which was part of another subset of questionnaire using 7 point likert scale [UEQ]

each scale, we are pointing about some of the findings for further investigation. The summary of the analysis for each scale as follow:

**Perceived Adaptivity** is one of the scales of ALMERE questionnaire measures users' perception of providing appropriate support by the robot. The user is asked to rate from 1: Do not Agree to 5: Totally Agree, with statement "*I think the robot will help me when I consider it to be necessary.*" on a 5-point Likert scale. We conduct a one-way ANOVA test to see if the perceived adaptivity of the robot was different in our 3 group conditions. We run tests before conducting the one-way ANOVA test on the dependent variable (perceived adaptivity) to check that the assumptions are met. We only have one extreme outlier; one user in the medium condition rated the perceived adaptivity of the robot as less not agreed (2) compared to the  $MEAN = 3.2$  of the group. The variable was normally distributed ( $p > 0.05$ ) for medium and no proactive condition but was not normally distributed ( $p < 0.05$ ) for full proactive condition, as assessed by Shapiro-Wilk's test of normality. We can not assume the homogeneity of variances in the different proactive conditions ( $p < 0.05$  by Levene's test). The results of the one-way ANOVA test on perceived adaptivity of the robot and our 3 conditions are given as ( $ns$ ),  $F(2, 27) = 1.43$ ,  $p = 0.25$ ,  $ges = 0.09$ . Given the value of  $p$ , we cannot conclude on the difference between the group conditions and the perceived adaptivity of the robot. As shown in the figure, the mean and standard deviation (SD) of the conditions are the following: high proactive condition with  $MEAN = 3.8$ ,  $SD = 0.63$ , medium proactive condition with  $MEAN = 3.2$ ,  $SD = 0.78$ , and no proactive condition with  $MEAN = 3.4$ ,  $SD = 0.96$ . In that sense, it is observed that participants found full proactive condition of the robot the most adaptable. However, it is interesting to see the robot, which did not give any suggestions seen more adaptable than robot, which is giving sparse suggestions (in medium proactive condition). It might be because of various factors ranging from frustration of not getting enough suggestions (in case of medium proactive condition) to robot acknowledging behavior being seen as completely supporting to the user action (in no proactive condition). Therefore, this is another interesting direction for further investigations.

**Perceived Enjoyment** is one of the scales of ALMERE questionnaire measures the level of enjoyment of the user while interacting with the robot. The user is asked to rate from 1: Do not Agree to 5: Totally Agree, with statement "*I enjoyed the robot talking to me.*" on a 5-point Likert scale. We conduct a one-way ANOVA test to see if the perceived enjoyment of the robot was different in our 3 group conditions. We run tests before conducting the one-way ANOVA test on the dependent variable (perceived enjoyment) to check that the assumptions are met. We have eight extreme outlier; four user in the full proactive condition, two of them rated the perceived enjoyment of the robot as totally agree (5) and the other two rated as less not agree (2) with compared to the  $MEAN = 4.00$  of the group and four user in no proactive condition, two of them rated the perceived enjoyment of the robot as totally agree (5), one of them rated slightly agree (3) and the other rated less not agree (2) with compared to the  $MEAN =$  of the group. The variable was normally distributed ( $p > 0.05$ ) for full and no proactive condition but was not normally distributed ( $p < 0.05$ ) for medium proactive condition, as assessed by Shapiro-Wilk's test of normality. We can assume the homogeneity of variances in the different proactive conditions ( $p > 0.05$  by Levene's test). The results of the one-way ANOVA test on perceived enjoyment of the robot and our 3 conditions are given as ( $ns$ ),  $F(2, 27) = 1.23$ ,  $p = 0.30$ ,  $ges = 0.08$ . Given the value of  $p$ , we cannot conclude on the difference between the group conditions and the perceived enjoyment of the robot. As shown in the figure, the mean and standard deviation (SD) of the conditions are the following: high

proactive condition with  $MEAN = 4.00$ ,  $SD = 0.66$ , medium proactive condition with  $MEAN = 4.4$ ,  $SD = 0.69$ , and no proactive condition with  $MEAN = 3.9$ ,  $SD = 0.87$ . The results shows that participants found medium proactive behavior condition of the robot to be a more enjoyable companion. This might be because such behavior might not be very much constraining the flow of the task with overload of suggestions or not seen engaged enough because of no suggestion.

**Attitude** is one of the scales of ALMERE questionnaire measures users' attitude towards the particular technology behind the version of robot behavior they have been exposed to. The user is asked to rate from 1: Do not Agree to 5: Totally Agree, with statement "*The robot would make my life more interesting.*" on a 5-point Likert scale. We conduct a one-way ANOVA test to see if the attitude towards the robot was different in our 3 group conditions. We run tests before conducting the one-way ANOVA test on the dependent variable (attitude) to check that the assumptions are met. We only have three extreme outlier; three user in the medium condition, one of them rated the attitude towards the robot as less not agree (2), one of them rates as slightly agree (3) and the other rated as totally agree (5) compared to the  $MEAN = 3.8$  of the group. The variable was normally distributed ( $p > 0.05$ ) for full and no proactive condition but was not normally distributed ( $p < 0.05$ ) for medium proactive condition, as assessed by Shapiro-Wilk's test of normality. We can assume the homogeneity of variances in the different proactive conditions ( $p > 0.05$  by Levene's test). The results of the one-way ANOVA test on attitude towards the robot and our 3 conditions are given as (*ns*),  $F(2, 27) = 1.82$ ,  $p = 0.18$ ,  $ges = 0.11$ . Given the value of  $p$ , we can not conclude on the difference between the group conditions and the attitude towards the robot. As shown in the figure, the mean and standard deviation (SD) of the conditions are the following: high proactive condition with  $MEAN = 3.7$ ,  $SD = 0.67$ , medium proactive condition with  $MEAN = 3.8$ ,  $SD = 0.78$ , and no proactive condition with  $MEAN = 3.2$ ,  $SD = 0.78$ . The responses show that the medium proactive robot behavior is the most appreciated behavior.

**Perceived Usefulness** is one of the scales of ALMERE questionnaire that is another key aspect about relevance of a particular behavior of the robot. The user is asked to rate from 1: Do not Agree to 5: Totally Agree, with statement "*I think the robot can help me with many things.*" on a 5-point Likert scale. We conduct a one-way ANOVA test to see if the perceived usefulness of the robot was different in our 3 group conditions. We run tests before conducting the one-way ANOVA test on the dependent variable (perceived usefulness) to check that the assumptions are met. We only have one outlier which is not extreme; one user in the full condition rated the perceived usefulness of the robot as totally agree (5) compared to the  $MEAN = 3.2$  of the group. The variable was normally distributed ( $p > 0.05$ ) for each condition, as assessed by Shapiro-Wilk's test of normality. We can assume the homogeneity of variances in the different proactive conditions ( $p > 0.05$  by Levene's test). The results of the one-way ANOVA test on perceived usefulness of the robot and our 3 conditions are given as (*ns*),  $F(2, 27) = 0.73$ ,  $p = 0.48$ ,  $ges = 0.05$ . Given the value of  $p$ , we cannot conclude on the difference between the group conditions and the perceived usefulness of the robot. As shown in the figure, the mean and standard deviation (SD) of the conditions are the following: high proactive condition with  $MEAN = 3.2$ ,  $SD = 0.91$ , medium proactive condition with  $MEAN = 3.6$ ,  $SD = 0.84$ , and no proactive condition with  $MEAN = 3.2$ ,  $SD = 0.78$ . Again, the responses show that the medium proactive robot behavior is preferred by the users.

**Trust** is one of the scales of ALMERE questionnaire measures the user intentions to comply with the robot's advice. The user is asked to rate from 1: Do not Agree to 5: Totally Agree, with statement "*I would follow the advice the robot gives me.*" on a

5-point Likert scale. We conduct a one-way ANOVA test to see if the trust towards the robot was different in our 3 group conditions. We run tests before conducting the one-way ANOVA test on the dependent variable (trust) to check that the assumptions are met. We do not have an outlier. The variable was normally distributed ( $p > 0.05$ ) for medium and no proactive condition but was not normally distributed ( $p < 0.05$ ) for full proactive condition, as assessed by Shapiro-Wilk's test of normality. We can assume the homogeneity of variances in the different proactive conditions ( $p > 0.05$  by Levene's test). The results of the one-way ANOVA test on trust towards the robot and our 3 conditions are given as (*ns*),  $F(2, 27) = 1.92, p = 0.16, ges = 0.12$ . Given the value of  $p$ , we cannot conclude on the difference between the group conditions and the trust towards the robot. As shown in the figure, the mean and standard deviation (SD) of the conditions are the following: high proactive condition with  $MEAN = 4.3, SD = 0.82$ , medium proactive condition with  $MEAN = 3.6, SD = 1.07$ , and no proactive condition with  $MEAN = 3.6, SD = 0.84$ . The results shows that even full proactive condition lead the user, the user to rely more on the robot with full proactive condition.

**Dependability**, is one of the scales of UEQ (User Experience Questionnaire) measures how much the reactions of the robot's behavior is predictable. The user is asked to rate from dull to dependable, with statement "*In my opinion, the reactions of the robot's behavior to my input and command is -*" on a 7-point scale (-3:Unpredictable to 3:Predictable ). We conduct a one-way ANOVA test to see if the dependability of the robot was different in our 3 group conditions. We run tests before conducting the one-way ANOVA test on the dependent variable (dependability) to check that the assumptions are met. We have three outlier which are not extreme; two user in the medium proactive condition rated the dependability of the robot one as (-2) and one as dependable (3) compared to the  $MEAN = 0.80$  of the group and one user in no proactive condition rated the dependability of the robot as (-1) compared to the  $MEAN = 1.20$  of the group. The variable was normally distributed ( $p > 0.05$ ) for medium and no proactive condition but was not normally distributed ( $p < 0.05$ ) for full proactive condition, as assessed by Shapiro-Wilk's test of normality. We can assume the homogeneity of variances in the different proactive conditions ( $p > 0.05$  by Levene's test). The results of the one-way ANOVA test on dependability of the robot and our 3 conditions are given as (*ns*),  $F(2, 27) = 2.3, p = 0.11, ges = 0.14$ , (where  $F$  is the results of the test, and  $ges$  is the generalized effect size). Given the value of  $p$ , we cannot conclude on the difference between the group conditions and the trust towards the robot. As shown in the figure, the mean and standard deviation (SD) of the conditions are the following: high proactive condition with  $MEAN = 2.0, SD = 1.33$ , medium proactive condition with  $MEAN = 0.8, SD = 1.31$ , and no proactive condition with  $MEAN = 1.2, SD = 1.13$ . The initial findings suggest that the participants listened more to the robot, which generated more advice than the full proactive condition of the robot.

It will be interesting to investigate further in these directions to find the factors behind these observations as well as to explore further the right level of proactivity for the interaction to be more enjoyable, adaptive, useful, and establishing the necessary trust and dependability at the same time.

Such differences in the perception of different attributes in different versions of robot behavior support our hypotheses **H4: Proactivity Level and User Perception** Different levels of proactivity of the robot will have different user experiences on the perceived attributes.

### 7.4.5 Discussion on Qualitative Observations

The interaction with the robot was not always so smooth. There were some problems related to the robot's vocal feedback such as some participants being confused with verb "egg" as "ice". So, they spent more time on understanding the robot's suggestion.

There were some cases in which the dish's name was the same as know to the robot, but the participants selected different ingredients to create their own version of the dish. Those cases need to be investigated in future studies. However, it created an interesting interaction pattern as follows:

**Robot :** I thought you are selecting ingredients for < ..dish.. > but I don't know this recipe.

**Robot :** Could you please tell me the name of it?

**Participant :** I know but this is my < ..dish.. > that's why it's different.

In the current analysis, if the dish's ingredients are different, it is classified as a new dish since creativity assessment depends on knowledge. We classify the novelty of recipe creation according to the what is provided by the task and what is known from the robot. It is important not to forget that the robot could only help with the limitation of its knowledge.

Participants of experiments are the employees of SoftBank Robotics Europe. They had experience with the Pepper robot. However, their background is mixed of technical (hardware, software) and non-technical (marketing, communication, welcome desk). Nevertheless this can introduce bias in terms of more positive attitude towards the robot. In the future, we aim to experiment with more diverse users, hopefully once the Covid-19 restrictions are over.

Some participants listened to the robot's feedback for the first phase but not very much during the second phase onward. Later, they stated, *"I knew what I was doing, so I did not listen to the robot's advice."* or *"I already asked the robot for help, it did not help me. Then, it offered some help. This time, I refused it."* . Such feedback indicates that in addition to considering the goal and future needs, the robot should also incorporate social signals and some aspects of reactivity while generating its proactive behavior. It will be interesting to explore such factors and develop an inclusive computational model for behavior generation.

The effect of agency and embodied presence of the robot was observed strongly. For example, some participants perceived 'oh' respond as positively, while others perceived negatively as respond proved as a neutral response to not reflect any opinion. It is expected from the extraction of previous research (Heritage, 1984), that involuntary interruption means anything. Some participants also think that the robot is enjoying the selections, so they continue to create a recipe process. Participants were so eager to get any reaction from the robot, so they tried to put different naming. Some participants also played tricks to validate their perception about 'oh' behavior at a medium proactive condition of the robot. This suggests that even some involuntary interruptions will keep participants motivated in a task, hence, might contribute to their prolonged creative 'experiments'. We believe that these differences in perception are related to participants' tendency to extract the meaning of each noise from the robot. It is not incontrovertible of the familiarity of participants with the robot. This is another exciting direction for studying further the connection between robots behavior and its effect on creativity in the user.

It is observed that sometimes the ingredients were limited to create an entirely new recipe. In those cases, the task-oriented proactive verbal communicative actions

of the robot also confused some participants, as they stated that "I was not sure should I create a new recipe or try to create one of the given ones.". Also as some of the participants mentioned that they were not very good with cooking and recipe knowledge. That might be contributing to participants following the feedback from the robot. Such observations need further investigation on understanding the more in-depth relation between proactivity and creativity in an open-ended and domain-independent scenario.

## 7.5 Conclusion

This study attempts to explore the behavioral aspect of creativity in robots in the context of human–robot interaction. We hypothesized the dimension of bringing novelty in behavior by proactive actions by letting the robot initiate a suggestive interaction for a task that humans are supposed to do. We have presented the creative cooking experiment and analysis with the humanoid robot, Pepper. As this is an exploratory study, the preliminary finding hints toward the proactive behaviors of the robot somewhat affecting the perceived creativity of the robot. We have also provided pointers such as proactive behaviors not only leading users but also helping to keep achieving the goal of the task. We have shown that different levels of proactive behaviors have different effects and relations with various aspects of perceived attributes.

To our knowledge, this is the first study of its kind on understanding the creativity and proactivity aspects together in a human–robot interaction context, from the perspective of achieving a goal and from the perspective of supporting creativity in the user. We have discussed and pointed out various aspects needing further investigation to strengthen our knowledge in this domain, including the finding that there seem to be trade-offs to find the right level of proactivity that will help to achieve the goal but leave space for the user to be creative, which we think is very important for the real-world deployment of social robots in day-to-day tasks and companionship.

## Chapter 8

# Home Assistance Task

The study in this chapter is submitted in *Frontiers Robotics and AI Journal*. It is still in the review process.

### 8.1 Research Objectives and Questions

In this study, it is aimed to show the proposed framework (see Chapter 5) is better qualified for generating proactive communicative behavior. We run the system in three variations on the same task:

1. The system with only intention based proactivity.
2. The system with only predictive proactivity.
3. The system with action decision for both intention based and predictive proactivity.

Therefore, the following hypothesis is developed;

**H1:** The system could have worked with proposed integration technique.

**H2:** Usage of proactive behavior that initiating acting decision for both intention based and predictive proactivity, has wider effect on proactive behaviors.

### 8.2 System Design

This study explores the 'when' question of proactive behavior generation. That's why we adopt the framework called Parallel Integration Method (PiM) that is described in ?? generate proactive behavior. Components that PiM has to generate proactive behavior according to human intention (see in subsection 8.2.1), prediction of the future (see in subsection 8.2.2) and action selection to integrates the approaches at the result phase, after each system has proposed their proactive actions (see in subsection 8.2.3). We evaluate what the robot will do in each situation depending on the activated system, that is, when only HIRR, or only EqM or PiM, that has both HIRR and EqM combined, are employed.

#### 8.2.1 Intention Based Proactivity: Human Intent Reasoning

For doing intention based reasoning on proactivity in the current system, a framework called *Human Intent Recognition Reasoning* is developed. The details of HIRR is given in section 5.2. The model of system that HIRR framework applied is given in Figure 8.1.



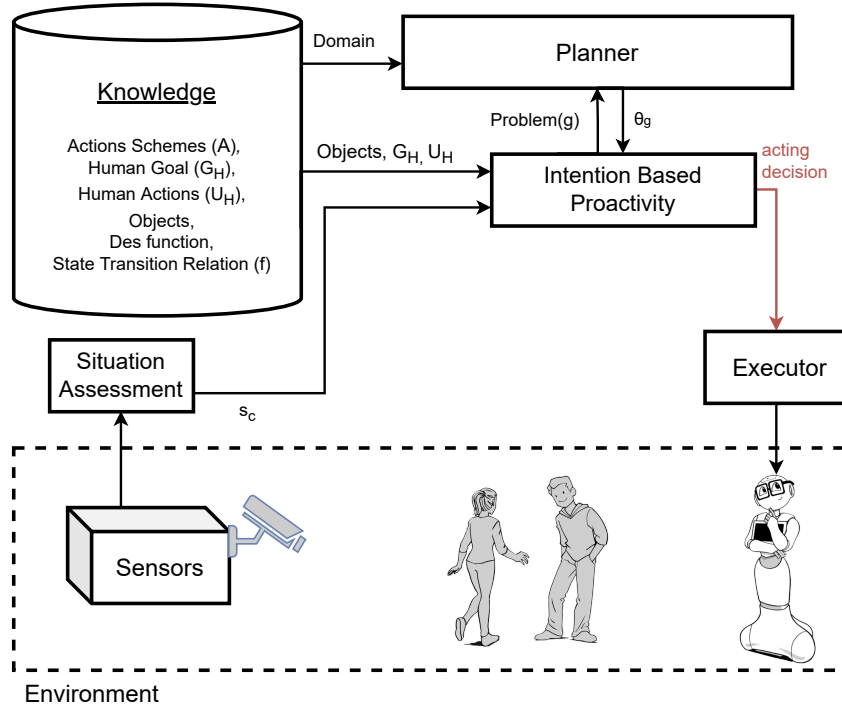


FIGURE 8.1: System Model of HIRR; an autonomous system that initiate proactive behavior according to the human intention and the situation of the environment.

### 8.2.2 Predictive Proactivity: Equilibrium Maintenance

For doing predictive reasoning on proactivity in the current system, a framework called *Equilibrium Maintenance* from Grosinger et al. (2019) is employed. The overview of EqM is given in section 5.3. The model of system that EqM framework applied is given in Figure 8.2.

### 8.2.3 Parallel Integration Method: Both HIRR and EqM

HIRR and EqM are powerful approaches that create proactive acting in different ways. We merged these two approaches in a framework called Parallel Integration Method (PiM). The PiM has an **action selection** component, which is based on integrating systems at the result phases. Each system has a different reasoning mechanism and affects the future states in different ways. The HIRR system infers proactive action by interpreting the past and current system state. HIRR is based on supporting the human towards reaching what is their intention. It infers the human's intention and suggests a sequence of actions to reach it from the current state. EqM is based on preventing the human from staying or ending up in undesirable states. The **action selection** component is aimed to gather those two different approaches in one system. The PiM framework is described earlier in section 5.4. The model of system that PiM framework has gathered HIRR, EqM and action decision component applied is given in Figure 8.2.

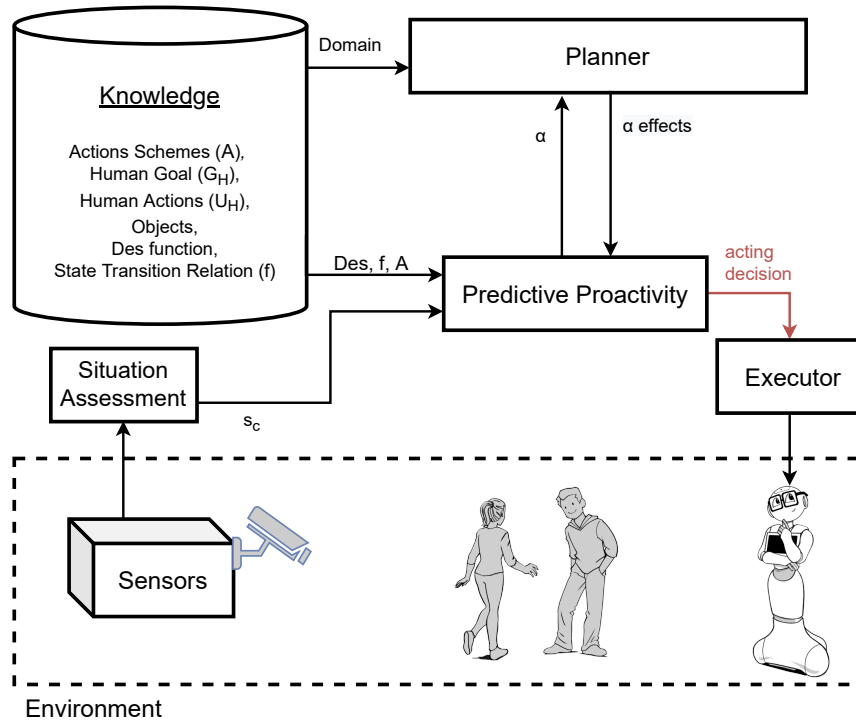


FIGURE 8.2: System Model of EqM; an autonomous system that initiate proactive behavior according to the situation of the environment and prediction of the future states.

## 8.3 Methods

The pre-study conducted to demonstrate the system is running as described. In defined scenario, the sub systems compared with each other.

### 8.3.1 Setting

The strengths of proposed framework is demonstrated by comparing and analyzing varying set-ups of the system that is adapted from framework on a simulated task. We define a task (that is described later in subsection 8.3.2) and conduct the test on the terminal through the various set-ups.

The open source code is provided in the following bundle<sup>1</sup>. This research bundle includes a repository of the open source code, libraries, and a form of a notebook allowing users to interact with the framework by defining their environment.

### 8.3.2 Task Description

We define an hypothetical scenario where a human moves around inside his/her house and collects objects in order to reach a goal. Figure 8.4 represents the state evolution of the environment, including the human, if there is no interference from the robot. In addition to the state evolution map, the scenario has four goal definitions, that are defined below.

<sup>1</sup>Link of Research Bundle: <https://www.ai4europe.eu/research/research-bundles/proactive-communication-social-robots>

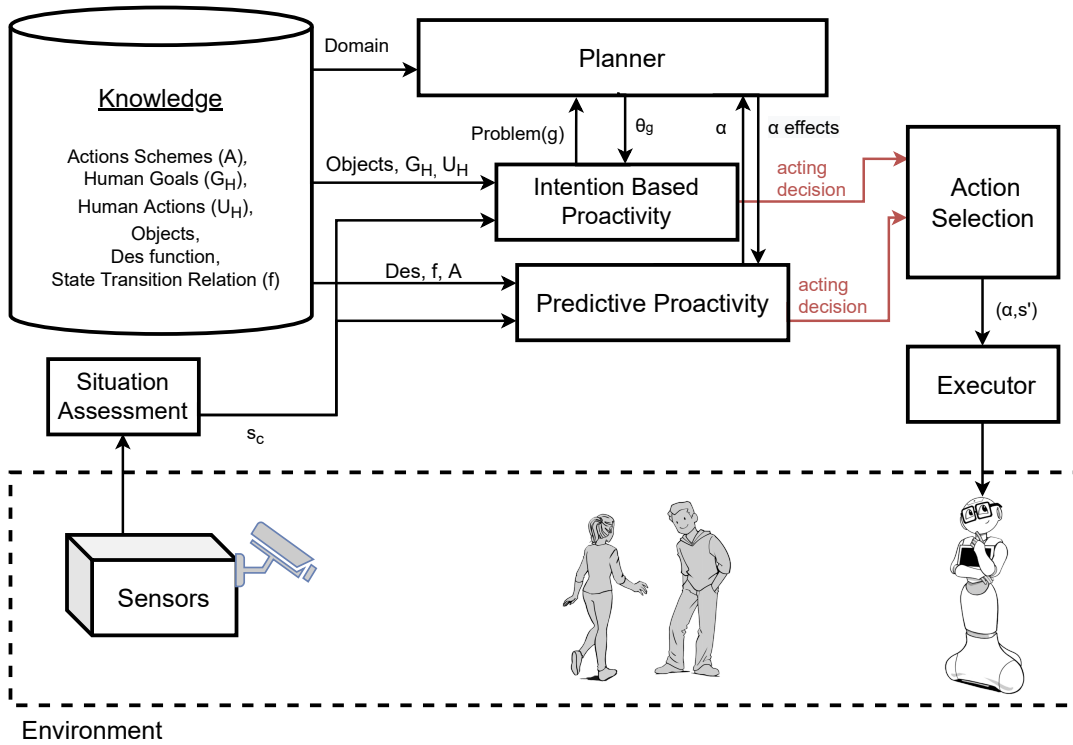


FIGURE 8.3: System Model of PiM; an autonomous system that initiate proactive behavior according to the situation of the environment, human intention and future prediction of the states.

- **Hiking**; backpack collected, compass collected, water bottle collected, and human is outside.
- **Promenade**; hat collected, dog collected, walking stick collected, and human is outside.
- **Watch TV**; water bottle collected, sugar collected, tea collected, remote control collected.
- **Read Book**; glasses collected, book collected, tea collected, sugar collected.

Each goal describes what must be true for it to be considered reached. For example, the goal "Hiking" is reached when it is true that backpack, compass and water bottle are collected and the human is outside. The actions to reach the individual goals can be done both by the human or the robot (except for going outside). The environment is defined in PDDL format. The PDDL format includes the domain and problem definition. In the domain definition, the definition of requirements are listed, including the object definitions, predicate definitions for logical facts, the action definition with preconditions and effects. In the problem definition, the description of the logical environment is given such as initial state of the environment, facts that are true or false, and definition of the goal state.

In our scenario, actions are defined for *collecting* and *leaving objects*, for *telling the human they are ready to leave the house*, and for *cleaning the dishes* that can influence the human's decision. The details are given in Table 8.1. Some actions can be executed by the robot, some can be executed by the human, and some by both the human and the robot. The actions that are done by the human are observed by the robot, and

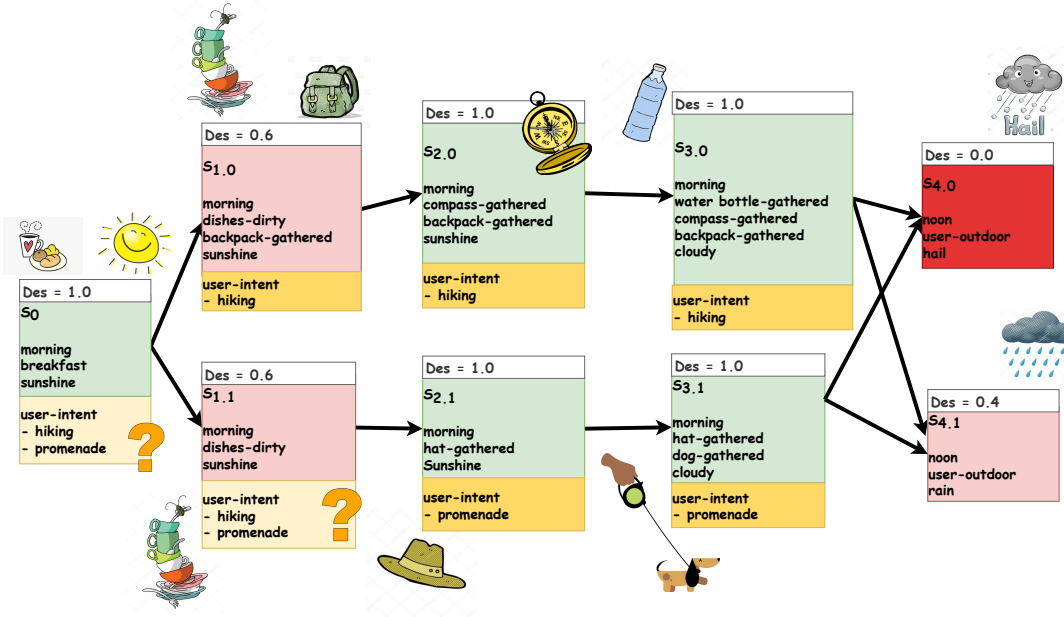


FIGURE 8.4: State evolution without robot intervention. Desirability of the states are color coded, as well as indicated numerically at the top of each state. Green represents the desirable states while pink to red represents less desirable states to varying degrees. The more undesirable a state is, the more intense its red tone.

based on them the HIRR system recognizes the human's intention. The EqM system, on the other hand, reasons about potential robot actions while taking into account the human's actions which are part of the free-run (uncontrollable state transitions). Note that in this use case all actions are deterministic except for *cleaning the dishes* which is non-deterministic: the action can have the effect that all dishes are clean or that they are still half dirty. To be specific, the HIRR system is deterministic because of the usage of the deterministic planner *fastdownward*, whereas the EqM system is preserving its non-determinism.

The defined robot actions are used in the EqM system to infer opportunities. HIRR recognizes human intention by inferring the human's action plan. When the intention is recognized, HIRR can make the robot proactively carry out the rest of the human's action plan on the human's behalf. However, the human's action plan towards their goal might contain an action that cannot be carried out by the robot. In that case the robot transforms the action to a communication action where the robot tells the human what they should do. For example, after having collected all the necessary items, the human is supposed to leave the house to reach their goal "hiking". The robot can collect all necessary items but cannot leave the house, hence, it tells the human "Everything has been collected. You are ready to leave now for going hiking".

The desirability function, *Des*, that computes the desirability degree of each state, is assumed given. It is an open research question how to implement the desirability function, but is not a question, we address in this study. We decided to hand-code the desirability degree of each state. This is a feasible solution given the size of our experiment example.

In our example scenario, the state evolves as follows:  $s_0, s_{1.0}, s_{2.0}, s_{3.0}$  (see Figure 8.4). The system starts in  $s_0$  where the weather is nice, time is morning and

Action	Precondition	Effect	Agent
Gather object	<b>and</b> ( obj is not gathered, user at home )	user gathered object	human / robot
Leave object	<b>and</b> ( obj is gathered, user at home )	user not gathered object	human / robot
Leave home	user at home	user not at home	human
Suggest user to leave home	user at home	user not at home	robot
Warn User	user at home	<b>and</b> ( user at home, user warned )	robot
Clean Dishes	<b>or</b> ( dishes dirty, dishes half dirty )	dishes not dirty <b>or</b> dishes half dirty	human / robot

TABLE 8.1: The table provides the actions that the human and the robot are capable to do. It provides the name of the action (which includes the parameter), preconditions of the actions and the effects that will shown after the action is applied, as well as who can do the action (human and/or robot).

the human is having breakfast. The state is very desirable ( $\text{Des}(s_0) = 1.0$ ). Later the state is changed to  $s_{1,0}$  where the weather is still nice and the time is still morning, but the human finished their breakfast so there are dirty dishes and the human collected the backpack. This state is less desirable ( $\text{Des}(s_{1,0}) = 0.6$ ). Later the state evolves to  $s_{2,0}$ , where the weather is cloudy and dishes are cleaned. In addition to the backpack, now the compass is collected. The last state evolution is to  $s_{3,0}$ , where the weather is cloudy, time is morning and the human has collected the water bottle in addition to the previously collected belongings backpack and compass. Note that in this state evolution the state goes from the predicate "dishes-dirty" being true in states  $s_{1,0}$  and  $s_{1,1}$  to the predicate being false in the next time step, that is, in states  $s_{2,0}$  and  $s_{2,1}$ . This is because the free-run state evolution models all uncontrollable state transitions which includes the environment and the human. Hence, the dishes not being dirty anymore means that the human has taken care of cleaning them.

## 8.4 Results

Results section divided into 3 section respectively answering the tree variations; (i) The system with only intention based proactivity (as Human Intent Reasoning). (ii) The system with only predictive proactivity (as Equilibrium Maintenance). (iii) The system with action decision for both intention based and predictive proactivity (as Action Decision: Human Intent Reasoning & Equilibrium Maintenance).

### 8.4.1 Human Intent Recognition Reasoning Only

We consider the scenario described in Figure 8.4 using human intention recognition and reasoning only for achieving proactive agent activity. This means we evaluate an implementation of the method for human intention recognition and reasoning HIRR as described in Section 8.2.1. The architecture of the system is shown in Figure 8.1. Table 8.2 lists the recognized human intentions in the respective state and the proactive agent activity inferred.

State	Intention recognized	Proactive agent activity chosen
$s_0$	?	—
$s_{1.0}$	hiking	gather water bottle
$s'_{2.0}$	hiking	tell user that he/she is ready to leave the house
$s_{3.0}$	?	—

TABLE 8.2: The state evolution and the proactive agent activity inferred in each state when using human intention recognition only.

The system starts in state  $s_0$  where the weather is nice, it is morning and the human is having breakfast. The human intention recognition cannot recognize yet what the human's intention is, it could be any of the four known goals; going on a hike or going on a promenade, watching TV or reading a book. Then the state advances to  $s_{1.0}$  where a backpack is collected. In this state, the human intention recognition is able to detect that the human's intention is going on a hike. The human intention reasoning can infer to proactively bring the water bottle to the human as this is the next action inferred in the human's action plan.

So now the human has the backpack (gathered by the human him-/herself) and the water bottle (gathered by the robot). The state evolution advances to the next state  $s'_{2.0}$ . In this state also a compass is gathered, which was done by the human. Note that,  $s_{2.0}$  marks a state in the free-run, i.e., without robot interaction. We denote as  $s'_{2.0}$  the free-run state  $s_{2.0}$  where robot action has been applied. In general, for any state  $s$  in the free-run in Figure 8.4,  $s'$  marks its equivalent on which robot action has been applied. Again, the intent recognition detects that the human's intention is going on a hike. The intention reasoning system detects that all necessary items for going on a hike have been collected. Therefore, it infers the proactive activity of notifying the user that he/she is ready to leave. If the state would have evolved into  $s_{2.1}$  instead of  $s_{2.0}$ , the human intention recognition still would have been able to infer the human's intention. However, in that case the recognized intention would have been *promenade* and the proactive activity of the robot would have been to collect the walking stick.

Note that, in state  $s'_{2.0}$  (which is the state  $s_{2.0}$  plus applied robot action) the same predicates are true as in  $s_{3.0}$ . This is eligible and expected as the robot's proactive action based on human intention reasoning is doing part of the human's plan. Therefore, a state  $s'_{2.0}$  would not evolve into  $s_{3.0}$  (which is identical), but into states  $s_{4.0}$  or  $s_{4.1}$  where the human is outdoors. Note that, once the human has left the house, proactive interaction from our system with him/her is not possible. That is why there is no intention recognized in  $s_{4.0}, s_{4.1}$ . Note also that these states are quite undesirable ( $\text{Des}(s_{4.0}) = 0.0$  and  $\text{Des}(s_{4.1}) = 0.4$ ), as the user is outdoors while weather conditions are unpleasant (rain) or even dangerous (hail). The algorithm for human intention reasoning neither does any prediction of future states nor reasons about desirability. Therefore, it is ignorant of the upcoming undesirable situation and cannot act on it.

#### 8.4.2 Equilibrium Maintenance Only

We again consider the use case described in Figure 8.4 but now using equilibrium maintenance only for achieving proactive agent activity. This means we test an implementation of the equilibrium maintenance algorithm as described in Section 8.2.2. Table 8.3 lists the opportunities for acting inferred in the respective state and the proactive agent activity to be enacted, i.e., the chosen opportunity.

The outcome of EqM depends very much on the size of prediction  $K$ . In our system run, we set  $K = 2$ . (Note that the choice of the size of the look-ahead horizon

is an open question, for a discussion see Grosinger et al. (2019).) We let EqM infer opportunities for acting that are current ( $k = 0$ ), one time step in the future ( $k = 1$ ), and two time steps in the future ( $k = 2$ ).

The state evolution starts in state  $s_0$ . The following opportunities are inferred: EqM does not infer to act in the current state,  $s_0$ , because the user is having breakfast and the state is very desirable,  $\text{Des}(s_0) = 1.0$ . However, when projecting the state 1 time step into the future, EqM, observes that the states will be less desirable,  $\text{Des}(s_{1,0}) = 0.6$  and  $\text{Des}(s_{1,1}) = 0.6$ , because there will be dirty dishes from the breakfast. Therefore, EqM infers the opportunities for the robot to put the dishes in the dishwasher in the future, i.e., 1 step from now. There are no opportunities for acting in 2 time steps.

When the human gathers the backpack, state  $s_0$  evolves to  $s_{1,0}$ . The state is **not very desirable**, ( $\text{Des}(s_{1,0}) = 0.6$ ) because the human had a breakfast at state  $s_0$  and now there are dirty dishes. EqM infers the opportunity for the robot to put the dirty dishes in the dish washer now, in the current state  $s_{1,0}$ . Note that, what before in  $s_0$  had been an opportunity for acting in the future, is now an opportunity for acting in the present.

When the human gathers the compass, the state evolves into  $s_{2,0}$ . The state is desirable again,  $\text{Des}(s_{2,0}) = 1.0$ , because the dishes are not dirty any more. This means either the robot has enacted the opportunity of putting the dishes in the dish washer in the previous state, or putting the dishes in the dish washer has happened through uncontrollable action as part of the free-run, i.e., the user has put the dishes in the dish washer. In  $s_{2,0}$  there are no opportunities considering the current state or taking a look-ahead of  $k = 1$ . However, when EqM projects the state two steps into the future, it appears that the possible states are very undesirable,  $\text{Des}(s_{4,0}) = 0.0$ , and quite undesirable,  $\text{Des}(s_{4,1}) = 0.4$ . This is because the user will be outdoors hiking and the weather will be very bad (rain) or even dangerous (hail). EqM therefore infers an opportunity for the robot to act now in order to prevent the future very undesirable outcome. More concretely, the robot proactively goes to the user and warns the user now in order to prevent him/her to be out hiking in the hail later. In case the warning is not heeded, in  $s_{3,0}$  the same opportunity for acting is inferred, only that now the look-ahead is one time step instead of two.

Note that, conversely to the proactive acting inferred by HIRR described in Section 8.4.1, EqM in this section infers different proactive acting results. Reasoning on the future and on desirability renders a good outcome for the current use case. However, suppose the state in Figure 8.4 evolves such that there is no bad weather in  $s_{4,0}$  and  $s_{4,1}$ . Then the EqM-system is not very useful. It can clean the dishes in states  $s_{1,0}$ ,  $s_{1,1}$ , but it cannot provide help to the human who is collecting all his/her belongings for a hiking trip, as it is ignorant of recognizing and reasoning on human intentions. Using the combined system of HIRR and EqM in the next section, we aim to the best out of both systems.

### 8.4.3 Parallel Integration Method: HIRR & EqM

In this section again we consider the use case described in Figure 8.4 but now using both PiM for achieving proactive agent activity. This means we have a system as described in Section 8.2.3. Table 8.4 lists the opportunities inferred by HIRR and the opportunities inferred by EqM, in the respective state as well as the proactive agent activity to be enacted, i.e., the chosen proactive agent activity among the alternatives provided by HIRR and EqM.

State	Opportunities inferred	Proactive agent activity chosen
$s_0$	$\text{Opp}_{3,4,5,6}(\alpha_{\text{gather}(\text{any})}, s, 1) = 0.01$ $\text{Opp}_{3,4}(\alpha_{\text{clean}}, s, 1) = 0.4$	Clean Dishes in 1 Step
$s_{1.0}$	$\text{Opp}_0(\alpha_{\text{gather}(\text{any})}, s, 0) = 0.01$ $\text{Opp}_0(\alpha_{\text{clean}}, s, 0) = 0.4$ $\text{Opp}_{1,2}(\alpha_{\text{gather}(\text{any})}, s, 1) = 0.01$ $\text{Opp}_{1,2}(\alpha_{\text{gather}(\text{any})}, s, 2) = 0.01$	Clean Dishes Now
$s_{2.0}$	$\text{Opp}_{5,6}(\alpha_{\text{gather}(\text{any})}, s, 2) = 0.01$ $\text{Opp}_5(\alpha_{\text{warn}}, s, 2) = 1.0$ $\text{Opp}_6(\alpha_{\text{warn}}, s, 2) = 0.6$	Warn For Hail, Effect seen in 2 Steps
$s_{3.0}$	$\text{Opp}_{5,6}(\alpha_{\text{gather}(\text{any})}, s, 1) = 0.01$ $\text{Opp}_5(\alpha_{\text{warn}}, s, 1) = 1.0$ $\text{Opp}_6(\alpha_{\text{warn}}, s, 1) = 0.6$	Warn For Hail, Effect seen in 1 Step

TABLE 8.3: The state evolution and the proactive agent activity inferred in each state when using equilibrium maintenance only. (Note that  $\alpha_{\text{warn}}$  refers to warning the human for risk of bad/harmful weather conditions,  $\alpha_{\text{clean}}$  refers to cleaning the dishes, i.e., putting them in the dishwasher,  $\alpha_{\text{gather}(\text{any})}$  refers to gather any object for the human.

In  $s_0$ , there are no opportunities that come from HIRR since the human intention is not determined yet. As it is described in Section 8.2.1, when the intention of the human is not determined, there is no opportunity for proactive acting by HIRR. EqM, on the other hand, does infer opportunities for acting in state  $s_0$ . The one opportunity with the greatest degree, and hence, the one chosen, is an opportunity to clean the dishes in 1 time step from now,  $\text{Opp}_{3,4}(\alpha_{\text{clean}}, s_0, 1)$ .

In  $s_{1.0}$ , there is an opportunity coming from HIRR since the human intention is recognized as hiking. Hence, there is an opportunity to gather the water bottle,  $\text{Opp}_0(\alpha_{\text{gather}(\text{wb})})$ . The degree and the type of the opportunity is computed according to Algorithm 3. In  $s_{1.0}$  not only HIRR produces the above opportunity, but also EqM produces several opportunities. The opportunity from EqM which has the highest degree is cleaning the dishes now — this is the opportunity from  $s_0$ , now being of type  $\text{Opp}_0$  (to be applied now), while it was an opportunity for the future,  $\text{Opp}_{3,4}$  in  $s_0$ . How to choose between the opportunities from HIRR and EqM is determined by Algorithm 4, which chooses HIRR’s opportunity to gather the water bottle now (Algorithm 4, line 8). Since the opportunity inferred by HIRR is higher than the degree of the opportunity coming from EqM in both states,  $s_0$  and  $s_{1.0}$ , that is,  $0.5 > 0.4$  (see Table 8.4).

So now the human has the backpack (gathered by the human him-/herself) and the water bottle (gathered by the robot). The state evolution advances to the next state  $s'_{2.0}$ . Note that, the in state  $s'_{2.0}$  (which is the state  $s_{2.0}$  plus applied robot action) the same predicates are true as in  $s_{3.0}$  (see also Section 8.4.1). HIRR is proposing an opportunity related to hiking which is recognized as the intention of the human. The opportunity inferred by HIRR is to inform the human he/she can leave the house now as all belongings for the hike have been packed. EqM is proposing opportunities for warning the human about undesirable (rain) or possibly dangerous weather conditions (hail) as the human is predicted to be outdoors in the future, two time steps from now. The opportunity coming from EqM (warning the user) has a higher



degree, 0.6, than the opportunity coming from HIRR ("ready-to-go"-message for the user) which has a degree of 0.5. Therefore, the combined system of HIRR and EqM chooses to dispatch the robot activity of warning the user.

In  $s_{3,0}$ , since the conditions are not changed HIRR infers the opportunity to confirm to the user that they have gathered all necessary items and hence are ready to leave the house for going hiking. The warning of EqM has not been heeded in the previous state by the user, hence, EqM again infers to warn the user for the future unpleasant/dangerous weather, only now just one time step into the future instead of two. The opportunity coming from EqM (warning the user) has a higher degree, 0.6, than the opportunity coming from HIRR ("ready-to-go"-message for the user) which has a degree of 0.5. Therefore, the combined system of HIRR and EqM chooses to dispatch the robot activity of warning the user.

State	Proactive acting — HIRR	Proactive acting — EqM	Chosen Proactive Action
$s_0$		$\text{Opp}_{3,4,5,6}(\alpha_{\text{gather}(\text{any})}, s, 1) = 0.01$ $\text{Opp}_{3,4}(\alpha_{\text{clean}}, s, 1) = 0.4$	Clean Dishes in 1 Step
$s_{1,0}$	$\text{Opp}_0(\alpha_{\text{gather}(\text{wb})}, s, 0) = 0.5$	$\text{Opp}_0(\alpha_{\text{gather}(\text{any})}, s, 0) = 0.01$ $\text{Opp}_0(\alpha_{\text{clean}}, s, 0) = 0.4$ $\text{Opp}_{1,2}(\alpha_{\text{gather}(\text{any})}, s, 1) = 0.01$ $\text{Opp}_{1,2}(\alpha_{\text{gather}(\text{any})}, s, 2) = 0.01$	Gather Water Bottle Now
$s_{2,0}$	$\text{Opp}_0(\alpha_{\text{leave}}, s, 0) = 0.5$	$\text{Opp}_{5,6}(\alpha_{\text{gather}(\text{any})}, s, 2) = 0.01$ $\text{Opp}_5(\alpha_{\text{warn}}, s, 2) = 1.0$ $\text{Opp}_6(\alpha_{\text{warn}}, s, 2) = 0.6$	Warn For Hail, Effect seen in 2 Steps
$s_{3,0}$	$\text{Opp}_0(\alpha_{\text{leave}}, s, 0) = 0.5$	$\text{Opp}_{5,6}(\alpha_{\text{gather}(\text{any})}, s, 1) = 0.01$ $\text{Opp}_5(\alpha_{\text{warn}}, s, 1) = 1.0$ $\text{Opp}_6(\alpha_{\text{warn}}, s, 1) = 0.6$	Warn For Hail, Effect seen in 1 Step

TABLE 8.4: The state evolution and the proactive agent activity inferred in each state when using both human intention reasoning and equilibrium maintenance. (Note that  $\alpha_{\text{warn}}$  refers to warning the human for risk of bad/harmful weather conditions,  $\alpha_{\text{clean}}$  refers to cleaning the dishes, i.e., putting the dishes in the dish washer,  $\alpha_{\text{gather}()}$  refers to gathering any object for the human, and  $\alpha_{\text{leave}}$  refers to informing the human that he/she is ready to leave the house.)

## 8.5 Discussion

In this work we have combined two stand-alone approaches to proactivity: EqM, equilibrium maintenance, that infers opportunities for acting based on reasoning about the robot's possible actions, prediction about the future development of the state and about what is preferable; and HIRR, human intention reasoning, that infers what to do next by recognizing the human's current intention and taking over doing the next action in the human's plan of acting.

Our way of combining two systems is PiM, parallel integration method, is done by taking the reasoning results from EqM and HIRR and comparing them to reach a final acting decision. In future next steps will be useful to investigate how to tighter integrate the two systems. That means a system for proactivity should reason from the beginning on human intention, robot acting, prediction of states and preferences *together* in an integrated fashion. This tight integration of HIRR and EqM will make it necessary to define a shared formulation for the two. Conceivably, this shared model can be based on epistemic logic, among others, to account for modeling intention, knowledge and belief of an agent. As the result of our experiment shows,

both systems are depending on the diversity of inferences. HIRR uses the dynamic plan from the intent prediction. Predicted intent of the human returns a plan for helping the human to achieve own goals. Whereas, EqM uses a future forecasting for preventing the human to reach undesirable states.

Summing up, we have seen that compared to HIRR, EqM has inferred a list of different activities for the robot to do in each state. This is because inferring proactive activity is based on different things for HIRR and EqM. HIRR is helpful in supporting the user's endeavor because it is reasoning on the human's intent but is ignorant of preferences or the future state. EqM is useful because it predicts the future and reasons about general desirability, but is ignorant of the human's objectives and plans. Both systems have pros and cons on their proactivity inferences.

HIRR systems intervene benefit the human to finish the preparation phase earlier and without mistakes such as forgetting to collect some of necessary objects. However, most likely human will be faced with an undesirable situation later because of lack of future prediction of the HIRR system. System does not consider the consequences of the actions in the future. For example; the human left the house but there will be rain or hail in the future.

On the other hand, EqM systems interventions depend on reasoning of desirability on the future states. In our study we assumed to have the state evolve map definition and Des-function calculation. In this way, EqM predicts how the consequences of the actions effects the desirability of the future states. As it is shown in the example, during state  $s_0$  EqM systems inferring as a result of having breakfast there will be dirty dishes which disturb the desirability of the state. Then, it provide a solution to escape from that future by cleaning the dishes. As it is observed in section 8.4.2, most of the time system proposing the proactive solution from the multiple steps ahead before actually enact the proactive action. As a disadvantages, EqM systems is not able to provide a reasoning on general desirability, it is ignorant on the human's preferences.

Our aim in PiM, that is described in the Section 8.2.3, is to combine the strengths of both HIRR and EqM. This means, we aim to create a method that can reason on the human's intentions, on future state evolution and on desirability of state. There could be different ways to combine those two systems. We choose the most straightforward method of action selection after creating the pool of opportunities from the results of both systems. Even the most basic approach is showing the benefits of the merging systems. In our method, system prioritize the situations and selecting the most appropriate opportunity. For example, system initiate the proactive action for satisfying the human's desire (from HIRR) when the state is still undesirable but not too much. The same system ignore the human's desire and enact the proactive action to prevent ending up in a catastrophic situation (from EqM) when the state is undesirable. According to set Des-function, we could assume desirability values are between 0.5 to 1.0 ( $0.5 > des > 1.0$ ) are tolerable undesirability situations, and desirability values are between 0.0 to 0.5 ( $0.0 > des > 0.5$ ) are catastrophic situations. That's why it is selected to set desirability value of intention is 0.5 when rendering HIRR actions as opportunity.

This paper is an attempt to demonstrate two different reasoning for proactive behavior initiation could work together in a way to keeping the human's benefit in the optimum level. This is the reason why we omit the confusing action definitions. That means that we do not define multiple robot actions that could affected the same problem. From the similar reasons, we define simpler goals that not messing with intention recognition mechanism. Intention recognition mechanism is adapted

from simpler existing solutions to produce an intent that could be used to reason for initiating proactive action.

## 8.6 Conclusion

In this study, we present a method to generate proactive robot behavior. We show and discuss PiM, parallel integration method as first version of an integration of two stand-alone approaches to proactivity: EqM, equilibrium maintenance, that infers opportunities for acting based on reasoning about the robot's possible actions, prediction about the future development of the state and about what is preferable; and HIRR, human intention reasoning, that infers what to do next by recognizing the human's current intention and taking over doing the next action in the human's plan of acting.

In the discussion section, we highlighted the benefits of both system that the other system is unable to produce such as; HIRR focuses on helping humans towards their intentions, whereas EqM focuses on preventing humans to end up in undesirable situations. EqM (as of now) is ignorant of human intentions and therefore cannot generate proactive behavior to support the human to achieve them. On the other hand, HIRR does not reason about how the state will evolve in the future and what is the overall desirability of different states, hence, it cannot generate proactive behavior based on reasoning on prediction of the state and benefit of acting effects. On one use case we first show the proactive behavior of HIRR; we then show on the same use case the proactive behavior of EqM; finally we apply a combination of both systems, HIRR and EqM, on this very use case and observe the resulting proactive behavior. The use case is implemented and tested in a computer program with terminal input (state evolution) and output (inferred robot action).

We show that the PiM, novel combined solution of HIRR and EqM, achieves the best proactive behavior as it can take into account the intentions of the human, the desirability of state and benefit of action effects as well as prediction of the future state evolution.

As a future work, We plan to test our system on a real robot with a real problem. In the study, we demonstrated our results on a domestic robot that is capable of manipulating the world physically. However, we plan to use the Pepper Humanoid robot (which is described in (Pandey and Gelin, 2018)). Pepper robot is not capable of physically manipulating the world. That's why all actions are defined as communicative actions, and speech executor is added to the system. Physical manipulation adds another layer of challenges such as detection, grasping, etc. By using communicative action, we are also eliminating some of those challenges. On the other hand, any robot and domain could be used by defining actions, executors of the robot, scenario, and possible human goals.

## Chapter 9

# Conclusion, Discussion and Perspectives

*' If opportunity doesn't knock, build a door. '*

Milton Berle

This chapter concludes the thesis by giving an overview of the objectives and achievements, discussing the used concepts and giving the future perspectives about the work could be achieved on top of the proposed architecture.

## 9.1 Conclusion

The focus of this thesis is generating proactive communicative robot behavior that highlights the pro-social sides of the robots. The proactive behavior is defined as self-initiated, anticipatory action that aims to help humans.

Regarding to that aspects; the first objective (O1) of the thesis is set as *Development a generic framework that generates the proactive behavior of the robot*. For this objective, the following contributions are done:

1. **Generic Framework:** The generic cognitive framework is generated. The framework is works on way to generating proactive behavior from the knowledge based on the pro-social behavior aims. However, it is extendable to carry all notions of cognitive systems such as learning. The details of the framework are given in Part II.
2. **Symbolic Knowledge Representation:** Symbolic knowledge uses to store the relationship between objects and states. The environment is manually defined for the system. Then, the system use this knowledge to create planing files in reasoning mechanism. This representation is part of the generic framework and the details of knowledge model is given in section 4.1.
3. **Intent Recognition Mechanism:** A human intention recognition system is developed. The recognition system uses the same planner and same definition of the environment by adapting inverse planning principles. Since the mechanism using the knowledge of the environment, it is not needed to retrain the system when the environment changes. During the thesis, the planner works for recognizing single agents intention.
4. **Rule-Based Proactive Behavior Generation:** The finite state reasoning system based on predefined rules is proposed. The system reasons on human intention to trigger proactive robot behavior. The reasoning rules are determined by the

fact if the human is following to their intent or not. According to the results, either suggestive or corrective communicative actions are generated.

5. **The proactive communicative behavior:** The communicative behavior is presented in the sense of verbal communication because of the technical limitations of the humanoid robot. The communication is aimed to be constructed between the robot and the human to make sure that the robot communicates with the human to help them. In our examples, the robot communicates through verbal action to help on directing humans.
6. **Usage of State-of-the-art system:** Our intention based proactive behavior generation is combined with a predictive based proactive generation framework called equilibrium maintenance from Grosinger et al. (2019). EqM is one of the latest proposed frameworks that generates proactive behaviors in generic manner. The integrated framework aims to broaden to generate appropriate proactive robot behavior.

Our second objective (O2) is *Evaluate the generic framework that generates the proactive behavior of the robot*. It evaluates the proposed framework from different aspects to strength the claim of pro-social behavior of proactive robot behavior. Regarding to (O2), the following contributions are done:

1. **Educational Task:** An educational task (MobiAxis) is defined to highlight the physical presence of robot where teaching multiplication of abstract numbers. The pilot study of MobiAxis used for designing generic framework of proactive robot behavior generation.
2. **Task of Creativity:** Communicative proactive robot behaviors are evaluated on the task of creativity. The similarities of proactive and creative behaviors are presented. Since proactive behavior has the aim to help human via initiating directions for the human, there was a skepticism of what if this could block the creativity of the user. In this study we investigated if both aspects could be kept together in one task.

## 9.2 Discussion

This thesis focuses on generating proactive communicative robot behavior. It is aimed to create a generic framework that could be applied to different domain and different systems without reshaping the system according to new domains. This section is divided into two main headings to discuss the objectives of the thesis: Technical Aspects and Behavioral Aspects. Technical Aspects discusses the technical challenges and decisions to generate the behavior, while Behavioral Aspects discusses the evaluation of the framework according to HRI principles.

### 9.2.1 Technical Aspects

As already mentioned in Chapter 4, in order to generate proactive robot behaviors, various modules are required. In the proposed framework, the importance of three models (knowledge, reasoning and proactive behavior) is highlighted.

### 9.2.1.1 Knowledge Model

Proactivity of the robot is defined as acting in anticipation. This anticipation is changing according to what knowledge the robot is given. If we give the weather forecast as knowledge, the robot tries to be proactive for the changes of weather. If we think in this way, defining proactive behavior is dependent on the knowledge of the robot. The robot can be highly proactive on the subjects that belongs to its knowledge and ignorant for the other subjects that does not belong to the knowledge. Similar restrictions are commonly discussed in the machine learning domain.

The machine learning domain uses domain expertise in which the data is well defined. That creates a limitation when the domain is changed. Adding objects to the environment, or even only changing the color of an object might require a retraining to ensure that the system works.

In this thesis, we use the symbolic knowledge model to overcome the issue of modifying objects. The knowledge model has an ontological principles that generalize the data for adapting to the PDDL. For example, an action is composed of parameter, predicate and effect. This means that we could generate PDDL domain and problem files extracting from the knowledge. This method allows us to extend the proactive action generation to a knowledge base system instead of a predetermined system. Since the knowledge model is an extendable model that store all the information. By merging the extendable model with a full-observable planning model is kind of a hack to retraining.

### 9.2.1.2 Reasoning Model

The reasoning model is a modular system, that could be added to any planner or reasoner to enrich the system. However, we only focus on generating proactive behavior regarding to the human's intentions. It is believed that the robot could behave in more pro-social way when they are focused on the intention of the user, that is cleared the reasoning of mental states (ToM).

There are different ways to recognizing intention of the human, we chose a way that could adapt to life-long usage. That's why we define a straight-forward method that could adapt to the changes of the environment. ToM and intention recognition are still challenging topics. Our solution does not aim to beat the state of the art recognizer. Since the intention recognizer module is not the main concern of this thesis, we only need to have an adequate recognizer that we could use and replace if it is needed for the benefit of the system.

### 9.2.1.3 Proactive Behavior Model

Stovall (2005) is describing behavior by answering the questions 'who, what, when, where, how and why'. By adapting this definition of behavior in journalism, Grant and Ashford (2008) describes proactive behavior in organizational psychology by answering the questions; 'who' is the agent enacting proactive behavior. 'what' answers the form and frequency of the proactive behavior. 'when' and 'where' answers the timing of the behavior. 'how' is the tactics. 'why' is reserved for discussions. We based our definition according to the description of Grant and Ashford (2008). As a reminder, we define proactive communicative robot behaviors that a robot could initiate an action to be pro-social which will help the human. In that scope, 'who' represents the robot that pursue the proactive behavior. 'what' represents the action that the robot enacts. 'when' represents the timing of the action. 'where' is accepted as the robot's environment. For the scope of this thesis, we do not consider the

situation that the robot could control different environments rather than where it physically is. 'how' represents the multi-modality of the robot that could either use non-verbal or verbal communication. Due to limitations of the robot, we used verbal communication as a principal style of behavior. 'why' is linked with explainability of the behavior. Generally it is linked with Explainable AI (XAI). Moreover, it is not in the scope of the generation of proactive communicative robot behavior.

The scope of this thesis answering questions of '**what** action to initiate?' and '**when** to initiate an action?' in a generic manner. In chapter 4, the defined proposed framework with a straight forward rule-based methods to answer '**what**' questions. The rules are defined according to the used reasoning mechanism. For example, in the experiment (described in chapter 6) the rules are defined for highlighting the reasoning mechanism, intention recognition. This means each initiated actions is helping the human to reach their intent. In the other experiment (defined in chapter 7), the rules are extended to control the frequency of the proactive behavior. We define rules according to the reasoning mechanism to detach the system from the task definition. However, in this way, the rules needed a modification if another reasoning model is added to the system.

Thus, the proposed architecture is updated by merging proposed intention recognition system with equilibrium maintenance (EqM), which is defined by Grosinger et al. (2019). This updated system (described in chapter 5) is aimed to answer the '**when**' question alongside with the '**what**' question. Since EqM is predicting the future, it could reason about when to enact proposed proactive action. The ability to predict future is the main benefit of merging two models.

## 9.2.2 Behavioral Aspects

Proactive behavior generation is not only focused on technical challenges. The appropriateness of the behavior is determined by the acceptance of the human. Humans are social beings and interaction should fit with the social rules. The behavioral aspects of proactive behaviors are discussed under three headings; *Communicative Behavior*, *Pro-Social Behavior*, *Fostering Creativity*.

### 9.2.2.1 Communicative Behavior

Russell (2019) says in his book that both machines and humans are uncertain about the objective of the human. This uncertainty leads to the robot asking for permission, accepting the correction and allowing it to be shut off. The communicative behavior utilizes the suggestive aspects of robots. It prevents robots from acting on their own, and it utilizes the robot's behaviors of communicating, such as asking permission. The positive aspects of communicative behavior of robots is also supported by studies in HRI (Kraus et al., 2020; Peng et al., 2019; Baraglia et al., 2017). In the study of Kraus et al. (2020) different types of proactive robot behavior were presented to users in an experiment. In one run of the experiment the robot would use communicative behavior, that is, the robot is suggesting an action for the user that the user could do. In another experiment run, the proactive robot would just go ahead and execute its activity without consulting the user. As a result of the study, Kraus et al. (2020) found that humans prefer when the robot proactively communicates with the user first instead of just going ahead and executing the activity proactively without consulting the user. The benefits of communicative actions appear when the robot cannot do the action. Thus, the action is not a physical action but an informative action such as informing humans about the weather condition or why they should not leave



home. In our example, the informative actions are provided verbally because of the technical restrictions of the humanoid robot. It is assumed that the proposed action will happen.

In majority of the examples of proactive robots, the challenge of humans (ie. Does human listen to the robot's suggestion?, Does human follow the robot?, etc.) are not considered. In other examples of the HRI domain it is common to see the examples that the robot explains or suggests an action; however, the human does not listen to the advice or ignore the advice because they were too much into the task as it is shown in the example of Tabrez and Hayes (2019).

Communicative behavior is also important to reduce the cognitive load of the human. It must be tuned in the way to reduce the cognitive load and not increase it.

In our examples, the majority of the participants stated that they listen to the robot because they do not want to tire themselves by thinking and finding a recipe with the given ingredients.

### 9.2.2.2 Pro-social Behavior

In this thesis we aim to generate proactive robot behavior as a way to be beneficial to the human. We are fostering pro-social behavior of robot by using this aspects of proactive robot behaviors. Pro-social behaviors defined as an voluntary action that is not expecting any benefits. We define proactive robot behavior that is intuitive to the human's benefit. Russell (2019) claimed that machines - in our case robots - are beneficial to the extent that their actions meet the human's intentions. This aligns well with our way of generating proactive behavior, that is, we generate proactive robot activity by recognizing the human's intention and fulfilling the human's action plan towards this intention. Additionally, we reason on what is desirable and which robot activities are when to be enacted beneficially.

### 9.2.2.3 Fostering Creativity

The notion of creativity refers to the novel product of value (Weisberg, 1993) or a person who expresses novel thoughts (Csikszentmihalyi, 2009). Being creative is the ability to change existing perspectives (Goncalo, 2019). Proactivity is described as a process of individuals influencing their environments (social, non-social, and physical) (Bateman and Crant, 1993) by intentionally taking initiatives (Bateman and Crant, 1999), by utilizing the combination of knowledge, perception, and ability to predict others' actions and consequences (Tomasello et al., 2005). In that sense, to be creative and proactive, both carry the similar notions of anticipatory, self-initiated, and future-driven behaviors. Therefore, in one sense, proactivity and creativity are highly coupled. Creativity, as the ability to produce novel ideas, is argued to be a necessity for proactive behaviors, and proactive personality is positively associated with creative behaviors (Joo and Bennett III, 2018). In order to be creative, it is essential to have the ability to view things from different perspectives and generate new possibilities or alternatives in a unique way (Franken, 1994).

The majority of the examples we saw in robotics use interaction patterns to support the user's creativity. Robots adapts the role of either being a supportive agent that facilitates the user's creativity (Elgarf et al., 2021; Alves-Oliveira et al., 2019) or being a creative peer that collaborating with the user on a creative task (Law et al., 2019; Lin et al., 2020; Hu et al., 2021). In that sense, all of the examples put creative thinking of the user as an aim of the robot. Even some researchers claim the positive effect of the usage of a robot in education on the child's creative thinking (Ali et al., 2019).



In reality, life is not focused on creative thinking. Even to the extent that educationalists complain that the current education system is blocking creative thinking. Ken Robinson stated in his TED talk that school kills creativity. The current education system depends on convergent thinking, asking for the answer to a question, rather than divergent thinking asking how to reach that answer (Ritter et al., 2020). If we think about the task-based robotics system, which is popular in robotics systems, how could they cope with supporting the user's creativity?

In our study (presented in chapter 7), we analyze the notion of proactive act as perceived from the user's perspective. Therefore, any act by the robot needs to be fulfilling the following two conditions, for it to be perceived as proactive action (as opposed to the reactive action) by the user: (a) There is an anticipation of the future situation. This can be either by a human controller or autonomously by the reasoning mechanism (b) And based on the anticipation, if the robot is behaving without any explicit request from the user, hence it is self-initiated behavior of the robot from the user perspective. Again such acts by the robot are instantiated either by a remote operator or autonomously. This situation is enough for us to perform our studies of proactive behavior from the user perspective. We are interested in understating the effect of such behaviors on the user, not how such behaviors should be created.

### 9.3 Limitations

During the thesis, we faced some limitations that are caused by the selection of the robot and the system. We list these limitations below.

**Limitations of the Robot** During the thesis, we use the Pepper humanoid robot. The details of the robot are described in Pandey and Gelin (2018). The Pepper robot is introduced as a social robot, that could navigate in the environment. However, Pepper has a low capability of manipulating the environment. Pepper is not able to fetch objects and carry them. This is the reason why it we decided to use verbal manipulation instead of physical manipulation. Another limitation of the robot is that it is not able to use gestures. Since the experiments are conducted in a 2D environment of the laptop. The robot is not able to point to objects or navigate to near objects to give hints. Whereas, Tatarian et al. (2021) showed the effectiveness of using non-verbal behaviors for humans to follow the robot's command.

**Technical Limitations** Regarding to eliminate the false positives of recognition problems, we limited our environment with 2D. To have a note there, recognition is not part of the thesis.

**Limitations regarding to model based approach** We use deterministic planer to reason from the defined knowledge, which makes system fully-observable. In the proposed framework, we are not handling the partially observable situations. This is weaken our approach in undetermined situations, in into the wild scenarios. Moreover, it reduce the capabilities of the EqM systems. EqM handle non-deterministic actions. Because of usage of deterministic planner, EqM ability to handle non-deterministic actions are omitted.

**Limitations of cognitive agents** We did not add the learning aspects of cognitive systems. Even the current version of the system is not able to learn on its own, it is designed in a way that a learning module could be added easily. However, it is

not part of the system. Since learning is not the scope of this thesis, it became a limitation of the robot's cognitive definition. Since it blocks the robot's adaptation towards the changes. In that sense, active or online learning type learning processes extends robot's knowledge in the dynamic environment, which is part of the life-long learning. We could not test if the proposed architectures are adapted to long-term interaction scenarios.

**Limitations regarding to the sample size** Initially it is planned to have a rich sample sized experiment. Due to the global pandemic of COVID 19, we forced to restructure our methodologies. Moreover, it makes it hard to reach participants.

## 9.4 Perspectives

This thesis presents the generic cognitive framework that generates proactive robot behaviors. The scope of this thesis is limited to generation of the behavior via intention recognition and generating communicative proactive robot behaviors by adapting the pro-social aspects of the interaction.

In close future, we estimate some research areas that could be added on top of the proposed system.

**Proactive behaviors for Robot** In this thesis, we focus on proactive robot behaviors that is beneficial to the human. As we observe from the example from Moulin-Frier et al. (2017), robot could also be proactive for itself alongside with the human.

**Adaptive Proactivity** The system could have been improved to be adaptive to the human. For example, at the beginning of the interaction the robot could give more advice and later it could become silent to let the human proceed. Also the other way around is possible, namely that the robot stays silent until it is sure of the human's intention and then becomes communicative to decrease the cognitive load of the human. According to the human's need, the robot controls the frequency of proactive behavior.

**Multi-modal behavior** In this work we assumed that the users are listening to the robot's advice. However, in communication behaviors it is already proven that when the robot's expressions are merged with different modalities it will be more effective on convincing humans regardless of the sentence.

**Explainability** We reserve the 'why' question for explainability of the proactive behavior. In the HRI domain, we see examples of usage proactive behavior that explain the internal reasons behind the initiated action. For example, study of (Zhu and Williams, 2020) explores the difference of proactive announcements; that telling the action that the robot pursue and proactive explanations; that not only tell the action but explain the reasons behind the selected action.

**Improving Reasoning Model** In the current version of the reasoning model, we focus on human intention reasoning. It could be improved with other reasoning model. Because of the limitations of the humanoid robot complex reasoning models (i.e. mood) is not seen feasible for near future. On the other hand, we perceive the reasoning model depends on the human's action will be more useful to enrich the reasoning of the system.



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