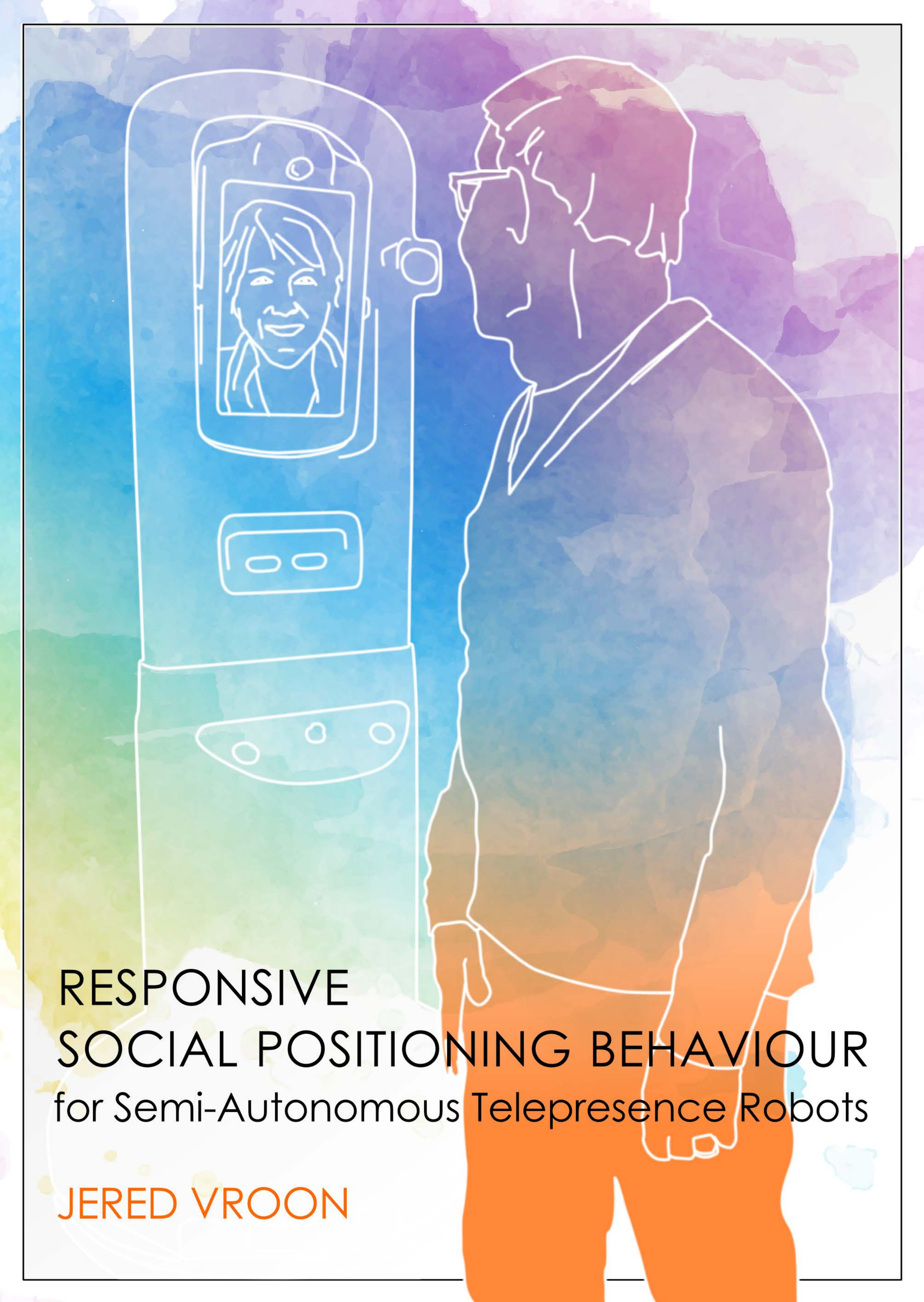

RESPONSIVE SOCIAL POSITIONING BEHAVIOUR for Semi-Autonomous Telepresence Robots

JERED VROON

RESPONSIVE SOCIAL POSITIONING BEHAVIOUR
FOR SEMI-AUTONOMOUS TELEPRESENCE ROBOTS

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RESPONSIVE SOCIAL POSITIONING BEHAVIOUR
FOR SEMI-AUTONOMOUS TELEPRESENCE ROBOTS

DISSERTATION

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by
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born on the 24th of June, 1989,
in Zutphen, the Netherlands

This dissertation has been approved by:
Prof. dr. V. Evers, University of Twente (supervisor)
Dr. ir. G. Englebienne, University of Twente (co-supervisor)

"It's all so huge and difficult. Like trying to travel through these mountains on foot.
The trouble is that essays always have to sound like God talking for eternity, and that isn't the way it ever is. People should see that it's never anything other than just one person talking from one place in time and space and circumstance. It's never been anything else, ever, but you can't get that across in an essay."
"You should do it anyway," Gennie says, "without trying to get it perfect."

— Zen and the art of motorcycle maintenance
Robert M. Pirsig

"Too Shakespearean"

— Vanessa Evers

ABSTRACT

What if a social robot could detect, from your body language, how you would like it to behave differently? We investigate how a social robot can find appropriate behaviour *through* the interaction, by reactively adapting its behaviours to social feedback cues. Or, in other words, by being responsive.

We focus our work on social positioning behaviours, a starting point for social interaction with any mobile robot, as they are particularly relevant to the Teresa project which forms the main context for this thesis. In the Teresa project, we worked on a mobile videoconferencing system, a telepresence robot, through which elderly can participate in joint social activities if they can not be present in person – for example, because of a contagious sickness, or because they just feel too tired. Preliminary studies have shown that manually controlling a telepresence robot distracts users from the social interactions the system is supposed to support. For that reason, within the Teresa project, we developed autonomous social positioning behaviours for the robot. As inappropriate behaviours by the robot might reflect badly on the person it represents, within this context it is especially important that those autonomous behaviours are appropriate.

Previous work has investigated and established various norms for social positioning that can be applied to robotics, such as proxemics. But when we look at social positioning behaviours in context, we observe various dynamics that would be hard to capture in such norms – such as people with hearing problems who, during some conversations, actively lean towards their conversation partners, to the point of getting what would otherwise be seen as intimately close. In addition, many of the established norms depend on factors that are hard to reliably detect in practice, such as hearing problems, gender, and cultural background. We pose that using responsiveness would allow a robot to find appropriate behaviours, even in these cases.

This work is a step towards further developing responsive positioning behaviour for social robots. Starting from the related work and various observations, with elderly and telepresence robots, we develop the idea of responsiveness. We then work out this idea into a formal model. From the model, we further investigate the detection of social feedback cues and possible adaptation strategies. Together, these form the first steps in the realisation of robot responsiveness – and perhaps, one day, these first steps will result in a small step back, taken by a robot that noticed it was too close for your liking and adapted its position accordingly.

SAMENVATTING

Hoe zou het zijn als sociale robot aan je lichaamstaal kan zien hoe jij zou willen dat hij zijn gedrag aanpaste? In dit proefschrift onderzoeken we hoe een robot de interactie met mensen actief kan gebruiken om gepast gedrag te vinden, door zijn gedrag reactief aan te passen aan de feedback beschikbaar in dergelijke sociale signalen. Of, in andere woorden, door 'responsive' te zijn in zijn gedrag.

We focussen hierbij op sociaal gedrag dat bepaalt waar een robot gaat staan tijdens interacties, positionering, aangezien dat het startpunt is voor sociale interactie met elke mobiele robot. Zo speelt positionering ook een belangrijke rol bij het Teresa project, dat de context vormt voor een groot deel van dit proefschrift, en waarin we hebben gewerkt aan een mobiel platform voor videobellen: een telepresentierobot. De visie van het Teresa project was om deze robot in te zetten in verzorgingstehuizen, zodat de ouderen aldaar ook deel kunnen nemen aan gezamenlijke activiteiten als ze niet fysiek aanwezig kunnen zijn, bijvoorbeeld door een besmettelijke ziekte, of doordat ze zich simpelweg te moe voelen. In ons vooronderzoek zagen we dat het handmatig besturen van een telepresentierobot onze gebruikers afleidde van de sociale interacties, terwijl die juist het hoofddoel zijn van het systeem. Daarom hebben we binnen het Teresa project verschillende modules ontwikkeld om autonoom sociaal gedrag voor positionering mogelijk te maken. Hierbij is het extra belangrijk dat de robot gepast positioneringsgedrag vertoont, aangezien ongepaste gedragingen door de robot een slechte indruk kunnen geven van de persoon die op het scherm van de robot te zien is.

De literatuur over dit onderwerp is voornamelijk gefocust op het onderzoeken en vaststellen van verscheidene sociale normen – 'regels' – voor positionering die kunnen worden toegepast op sociale robots, zoals bijvoorbeeld 'proxemics'. Maar wanneer we naar positioneringsgedrag in natuurlijke interacties kijken, zien we een rijke dynamiek, die moeilijk in zulke regels te vatten is; zo zagen we mensen met gehoorproblemen vaak naar elkaar toe leunen terwijl ze praatten, daarbij zelfs intiem dicht bij elkaar komend. Daarnaast vonden we dat veel van dergelijke regels afhankelijk zijn van factoren die in de praktijk moeilijk herkenbaar zullen zijn voor een robot, zoals gehoorproblemen, geslacht en gender, cultuur en achtergrond. Daarom verwachten wij dat, in dit soort situaties, niet regels, maar juist 'responsive' gedrag een robot kan helpen gepast gedrag te vinden.

In dit proefschrift werken we aan de ontwikkeling van zulk 'responsive' gedrag voor sociale robots. Op basis van literatuuronderzoek en verscheidene observaties, zowel met ouderen als met telepresentierobots, ontwikkelen we het idee achter 'responsive' gedrag. Dit idee werken we uit tot een formeel model, dat we vervolgens gebruiken om te kijken naar twee essentiële onderdelen; het herkenen van feedback aan de hand van sociale signalen en verschillende manieren waarop een robot zijn gedrag in reactie daarop kan aanpassen. Dit zijn de eerste stappen voor het realiseren van 'responsive' gedrag voor sociale robots – en wellicht zullen deze eerste stappen ooit leiden tot een kleine stap terug, genomen door een robot die merkte dat jij hem ongepast dichtbij vond komen en vervolgens besloot zijn gedrag daarop aan te passen.

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Doing a PhD has been an amazing journey. It has also been a lonely one; somehow the process of absorbing yourself in a single rather specific topic can feel a bit like an exile. For that reason, I here want to try and thank all the people who have been with me in these past few years.

For my family, that has accepted that I don't always talk as often with them as we would like – but never has ceased to be happy when we *do*. I am grateful for the never-ending faith you have in me, especially in those situations that I did not feel it myself. I will always feel intensely at home with all of you.

Thank you, Roos, Marieke, Theo, and Jelle, for all the pleasantly complicated absurdism, 'situations', wild creativity, walks, long conversations, performances, emails, projects, and games.

Saskia, thank you for teaching me that you can also solve problems by trying to change the world around you. For the time we shared, and all the questions we asked each other.

Heleen, thank you for teaching me that it can be a relief to occasionally handle your problems by complaining about them with friends. You have pushed me for the better in the time we shared.

And Roos (yes, you are in here twice), thank you for letting me share in and learn from your beautifully balanced mix of listening and speaking.

I am immensely happy and grateful to have been a part of the local student theatre association, NEST. Because I have truly enjoyed playing roles in the different plays – from uptight wall to aggressive angel and escapist puppy. Because I have truly enjoyed the year in which I was allowed to direct the TheatreLab. And most of all because of the amazing warmth and the group-feeling that is carried by all members and directors of NEST. Special thanks go to the Order of the Stone, our role-playing and general goofery have been a very pleasant distraction.

What worked?
What would you like to know more about?

I am similarly grateful for the local student dance association, Arabesque, which has provided me with a perfect mix of both the creative and the more technical aspects of modern dance. Exploring movement has been a joy each and every time. I specifically want to thank Laura – for the dances we choreographed together, for being an amazing secretary – and Henk – for being our pleasantly calm down-to-earth treasurer.

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Vanessa, thank you for trusting me to do my own thing; I think you have an amazing desire to be involved in and dedicated to everything going on, even though that fills your agenda well beyond the brim. Gwenn, you only came on board when I had already had well over a year to start deviating from most things machine learning and still picked it up graciously. Thank you for listening to my weekly updates, for reading my work, and for your many thoughtful and intelligent comments and suggestions.

And, lastly, thank you – whoever you are – for reading this thesis. Despite the lonely bits, I have enjoyed making this stack of paper[1]. I hope you will enjoy the pieces that you read.

1 Or, this huge file, if you are reading this digitally.

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In this chapter, we introduce the concept of responsiveness; adapting to social feedback cues – not to 'learn', but as part of the social dynamic. Based on this concept, we then discuss the main questions around which this thesis is structured and the contributions that it aims to make.

1 INTRODUCTION

> On stage, the actor playing Michael is expressing his righteous anger. His body tense, as if any moment he could hit someone. He moves closer, his face only inches away from that of his adversary. Through clenched teeth, he snaps out the words, "what foul play, what malevolence drives thee?[1]" The adversary looks back, casually picking her nose.

As demonstrated by this example, it is crucial, in acting as well as in dance, that the performers pay attention to each other, working together to create the interactions that make the performance. If you want to make a situation feel scary to the audience, it is not enough that one actor looks angry and aggressive – it is only when the other actors act afraid in response that things start feeling dangerous.

In natural interaction, this dynamic of actions and interactions is similarly important, with a strong experiential aspect; imagine the difference between expressing anger (or another emotion) at someone who does respond to you, or at someone who ignores you completely. Or, to give an example from previous research, it is not the distance that best predicts the success of a speed date – it is the variance of that distance during the interaction [97]. In other words, the big and small ways in which people respond to us can feed back into our own system, influencing our own behaviour and attitudes, consciously or subconsciously.

We will refer to these dynamics as **responsiveness**; adapting to social feedback cues – not to 'learn' new general rules for future behaviours, but to adapt specifically to the current social dynamic. While we will later specify responsiveness in more detail, the core idea of this thesis is that mutual responsiveness could allow social (robotic) agents to engage in a dynamic that provides meaning to our interactions. At the most basic level, the dynamic afforded by mutual responsiveness can be a back-and-forth. Yet, at the same time, it is easy to imagine mutual responsiveness resulting in a rich social 'dance'; a dance in which we develop in-jokes and create unique interactions through interacting, while slowly getting closer to each other.

This thesis is dedicated to further motivating, specifying, implementing, and evaluating this concept of responsiveness in the context of social robotics.

1 Loosely translated from Lucifer, by Joost van den Vondel (first performed in 1654).

1.1 RESPONSIVENESS FOR SOCIAL ROBOTICS

Social robots, actuated machines that deliberately interact with humans[2], are becoming more and more prevalent. These social robots are diverse, with a wide variety of intended user groups, hardware, and functions; what they do have in common is a need for behaviour that supports the intended interaction.

Consider, as an example of a social robot that will play a formative role in this thesis, the TERESA project [86] (see Figure 1). Mobile Robotic Presence systems (**MRPs**) consist of a teleconferencing system mounted on top of a mobile, robotic, base [55]. TERESA is an MRP that allows elderly to visit activities from a distance, if they cannot do so in person. The aim of the TERESA project was to try and develop semi-autonomous behaviours to take care of low-level social control, allowing the controller of TERESA to focus on their friends, peers, and family.

There is a wide and diverse range of other work that investigated which behaviours are suitable for social robots (**socially normative robot behaviour**): From robots that adapt their gait to be more synchronized with the person they are following [42], to robots that try to support effective learning from learning materials [24]. From seal robots that invite petting, and help elderly with dementia to open up [81], to large mobile platforms that guide people in museums [47] or around airports [94].

1.1.1 *Focusing on social positioning*

Robots are very diverse in the functions they fulfil – but many of those functions depend on the capacity to move around. Allowing elderly to participate in social activities through an MRP? Guiding people in museums or around airports? Approaching people to give them information? Fetching objects and bringing them to people? All these functionalities will require a robot to move around.

When locomotion happens in interactions with people, it is important to consider which positioning behaviours are considered to be socially normative (**social positioning**). Because a robot might otherwise offend people, or miss out on opportunities to smoothen the interactions it is to engage in. In other words, locomotion should in interaction be considered as a social behaviour, as we will discuss in more detail in Chapter 2.

2 There are many different ways in which the term 'social robot' has been defined (e.g. [6, 14, 28, 90]). Within the context of this thesis, we will use this broad and pragmatic definition as it seems to encompass most of what currently is perceived as a social robot. As every definition, it has its own peculiarities; e.g. it excludes most vacuum cleaner robots since their interactions with humans (albeit commonly responded to as if social [88]) are usually not deliberate by either the developers or the robot itself.

Figure 1: TERESA being used by elderly to connect with their peers and family.

In this thesis, we will focus on social positioning, because of its functional and social relevance, but also because it seems particularly well-suited for responsiveness (Section 2.2). More specifically, in this thesis we will focus in particular on social positioning with roughly human-sized mobile robots that position themselves by driving. Such a specification is necessary because robot size may well influence social positioning [36, 104], and also because, intuitively, the perception of social positioning may also change if other, less common, forms of locomotion are used, such as walking on robotic legs.

Of course, this focusing of the scope is not to suggest that responsiveness is limited to the same scope in its applicability. On the contrary, we will discuss several instances of approaches within wildly different fields that fit our definition of responsiveness (Section 2.3).

1.1.2 *Research questions*

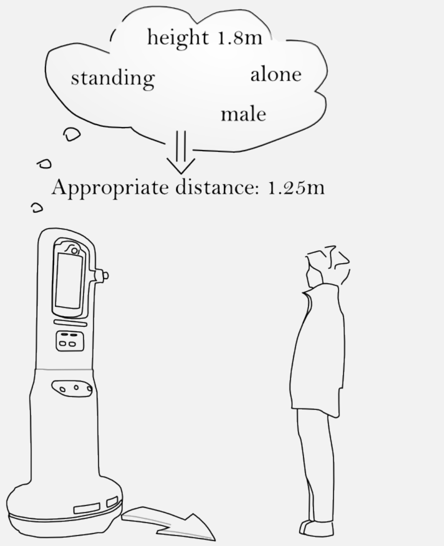
In this thesis, we will formally define responsiveness as a form of behaviour generation that tries to *continuously adapt the behaviour* of an agent based on *observed social feedback cues* (Chapter 4). While there exist social robots that use feedback to improve their behaviour (e.g. through online learning), as well as social robots that continuously adapt their behaviour based on immediate cues (commonly referred to as **adaptiveness**), the combination of these two aspects in responsiveness allows for a specific and novel dynamic (Box 1 illustrates this). As we will argue in this thesis, being on the intersection of these approaches allows for a specific kind of short feedback loops, which make for an informative and effective dynamic of improving the behaviour of an agent *through* the interaction.

Apart from the intrinsic value that embracing responsiveness could have for dynamic interaction, it may also allow a social robot to establish/negotiate its needs through its behaviours. We will illustrate this with one example. A common approach in the development of

Four ways a robot can decide to move closer

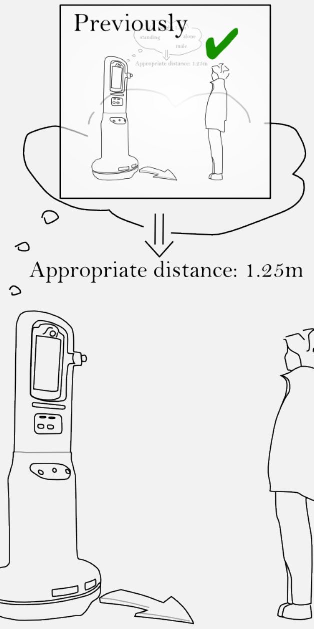
Even if robots show the same behaviours, they can still use different underlying reasoning. Below, we give examples of four kinds of reasoning discussed in this thesis, all resulting in the robot deciding to move a bit closer.

Setting-specific



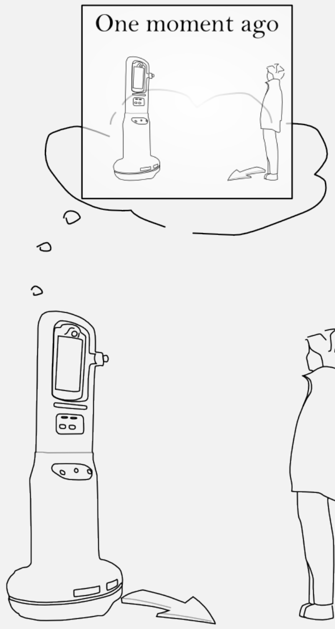
"I think they're male, 1.8m tall, alone, and standing. Based on my prior knowledge, I should move to 1.25m."

Learning



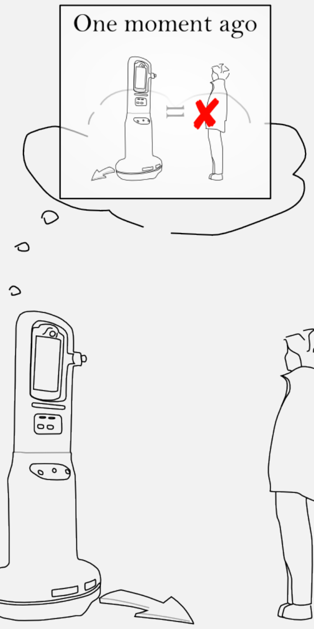
"I think they're male, 1.8m tall, alone, and standing. As learned from earlier interactions, I should move to 1.25m."

Adaptive



"Environment noise just increased; I should compensate by moving closer.

Responsive



"They seemed unhappy with my behaviour when I moved back just now; I should compensate by moving closer."

Box 1: Illustrating different approaches to approaching someone robot behaviour is to view it as a static; depending on a range of factors in the setting, a particular behaviour is considered to be suitable (we will refer to this as the **Setting-specific approach**). One specific case of this view can be found in a range of work arguing that it is undesirable for robots to get closer than a certain distance of people (e.g. [13, 43, 91, 93, 104]). Viewing this distance as something that is fixed/static would imply that a social robot should not get closer, which can pose various challenges, e.g. for navigation [61], interaction [41], and perception [67, 69].

Within this thesis, we will investigate whether using a responsive interaction dynamic can allow for treating this distance as something that is established – or negotiated – through the interaction. To this end, we will take several steps, guided by two main questions (see Table 1 for an overview).

For our first question, we will look further into social positioning for mobiles robots. While we started with an open exploration, based on both previous literature and a range of observations in the context of Teresa, our early findings suggested, as also argued above, that there was a dynamic back-and-forth that played a key role in social positioning. This exploration is roughly captured by the following question, which we investigated both for interactions with and interactions without a social robot:

Research question 1 What dynamics play a role in social positioning?

We will then propose responsiveness as a theoretical framework suiting those dynamics, a proposal that we will put to the test with our second question. On the one hand, we will investigate if it is possible to build the components necessary for an effective responsive system. On the other hand, we will investigate how such responsive behaviours – and, by extension, interactions with such a responsive system – would be perceived by people; how will people respond if a robot makes a social faux-pas, and how if it then tries to correct its behaviour? These investigations are roughly captured by our second research question:

Research question 2 Can we use responsiveness for effective social positioning?

Together, these two questions will provide a thorough investigation of responsiveness, in terms of both the dynamics involved in social positioning it could fill and its potential to actually do so. As such, these two questions will provide the basis for the more specific quantitative and qualitative questions that we will ask in the following chapters.

1.2 STRUCTURE OF THE THESIS

To investigate the opportunities for responsiveness, we will first discuss the role it could play in social interactions – by looking into the

Chapter	Outline	
1	Introduction	
2	**Research question 1** What dynamics play a role in social positioning?	Approach 1: Theoretical background of (dynamical) social positioning behaviours
3		Approach 2: Contextual analysis in the context of TERESA
4	Formalizing responsiveness as a paradigm/architecture to implement those dynamics	
5	**Research question 2** Can we use responsiveness for effective social positioning dynamics?	Requirement 1: Can we detect social feedback cues?
6		Requirement 2: Can we define suitable improvement strategies?
7		Requirement 3: Should a robot respond to feedback with an improvement strategy?
8	Conclusions and discussion	

Table 1: Outline of the research work discussed in this thesis and the questions that guided it. Research questions are specified and motivated in more detail in the chapters where they are discussed.

dynamics that play a role in social positioning for robotics. The theoretical background to our work (Chapter 2) will try to identify this role in the existing literature, arguing that a large part of prior work on social robots is non-responsive, and discussing how work on social positioning in human-human interaction involves specific interaction dynamics. To give these theories a grounding in reality, we will then report on several exploratory studies and a data collection (Chapter 3) that similarly indicate the relevance of such interaction dynamics, in interactions between humans and robots. Most of this work has been conducted in the context of the aforementioned TERESA project.

We will then give a formal definition of responsiveness fitting that role, as a reactive approach to optimizing social normativity (Chapter 4). This formal definition allows us to make the concept more specific, more applicable, and to identify relevant requirements for implementing responsiveness. Since responsiveness is a particular way of generating behaviour, it can be described as an Action-Perception loop – specifically one that places emphasis on very thin slices of the interaction. As we will argue in this chapter, to do so, responsiveness needs to specifically detect low-level non-verbal cues that immediately reflect how the interactee felt about the agents' previous actions (**social feedback cues**). And, likewise, responsiveness needs specific actions that can be used to immediately adapt behaviours based on those cues (**improvement strategy**).

Based on these definitions, we will then discuss the implementation of responsiveness and its necessary components. To start, we will discuss the detection of social feedback cues (Chapter 5), which we implemented for the specific case of detecting the appropriateness of different interaction distances based on tracking the position and orientation of head and upper-body. To train this detector and find potentially relevant social feedback cues, we collected a dataset through an experiment. We will then investigate improvement strategies (Chapter 6), independent from social feedback cue detectors, by giving a theoretical overview and discussing a small-scope Wizard-of-Oz experiment investigating the effectiveness of using different improvement strategies to adapt to hearing problems.

We will then discuss our investigation of a key assumption of responsiveness; do people, indeed, evaluate it as appropriate when a robot responds to a social feedback cue on its social positioning behaviour by using an improvement strategy (Chapter 7)? Specifically, we conducted a video study in which we looked into the effects of different aspects of social positioning by a robot – either in line with responsiveness or not – on perceived appropriateness of those behaviours.

In closing, we will wrap up our findings and conclusions, and discuss various ways in which responsiveness could be used in further development (Chapter 8). Among others, we will discuss how responsiveness could be implemented and how it could be applied beyond social positioning.

1.3 CONTRIBUTIONS

We feel the main contribution of this thesis is the concept of responsiveness that we work out in detail, which could be used to give machine intelligence the capability to adapt to social feedback cues. On the one hand, this fleshing out entails an investigation of the dynamics responsiveness could be used to represent in the context of social positioning with robots. On the other hand, it entails various efforts into implementing and testing responsiveness, demonstrating that all requirements for creating responsive robots can be met. As such, the work collected in this thesis constitutes a starting point for applying and implementing responsiveness; providing various handholds for deciding when to use responsiveness and when not to use it, and for implementing responsiveness in context.

Various parts of the work we conducted may also be a contribution when considered in their own right, i.e. independently from responsiveness. Our assessment of the context of social interactions with a semi-autonomous telepresence robot (Chapter 3) identified various factors that can play a role in, among others, acceptance and perception of social robots and the remote user of MRPs. We collected two, publicly available, datasets on social positioning behaviours of people interacting with social robots (Chapters 3 and 5). Within our theoretical framework, we identified various limitations of a setting-specific approach to social behaviour generation (Chapter 4). We showed that social feedback information can indeed be detected from non-verbal behaviours, by implementing the first version of a social feedback cue detector (Chapter 5). We tested improvement strategies in context, demonstrating not only their applicability (Chapter 6) but also that they could be used to improve the perceived appropriateness of an agents (approach) behaviour (Chapter 7).

This research is a step towards further developing responsiveness for social robots – 'artificial responsiveness'. And perhaps that first step will eventually result in a small step back, taken by a robot in response to an actor trying to express his emotion, working together to create the interaction.

In this chapter, we give an overview of the previous work on social positioning, both in human-human and human-robot interaction. We find an overall development from more static accounts of social positioning (e.g. specifying which approach distance to use) to more dynamic accounts (e.g. studying and using the communicative aspect of changing positioning during an interaction). In addition, we discuss different social cues that play a role in such dynamic accounts of social positioning, and selected examples of how suitable behaviours could be found through the interaction.

2 SOCIAL POSITIONING – A THEORETICAL BACKGROUND

> There is a theatre exercise that clearly demonstrates the relevance of social positioning. (1.) Have two people stand roughly 3 meter apart, (2.) have one of them say a sentence, any sentence, (3.) have that person take a step towards the other person and then repeat that same sentence, (4.) repeat step 3 until their noses are almost touching. As you do or observe this, you will notice that with every step the load of the sentence changes. The volume, pitch, and speed with which the sentence is uttered usually changes, and so do the posture of both the speaker *and* the listener[1]. Duos start giggling, or tension builds between them. On a gut-level, there is a massive difference between someone saying "Thank you" while they are standing at the other end of the room, as opposed to them saying the same while their nose is almost touching yours.

In this chapter, we will give a theoretical background for social positioning in human-robot interaction. To do so, we will first outline the development of theories about and studies into social positioning in human-human interaction (Section 2.1). We will then discuss how these theories and results were used for the development of social positioning behaviours for social robots (Section 2.2). A recurring pattern in this literature is a gradual development from more static approaches to more dynamic approaches. While we argue later on in this thesis that responsiveness could be such a dynamic approach, there exists no prior general framework for responsiveness yet. Instead, we will give an overview of strategies bearing similarity to responsiveness, that have been applied effectively in a range of fields (Section 2.3).

2.1 HUMAN SOCIAL POSITIONING

Social positioning in human-human interaction has been extensively researched; starting around the 60s, and having developed to well over 700 papers at the end of the 80s. We will here give a brief overview of these developments, starting with the early theories that tried to capture social positions (Section 2.1.1). These theories sparked a

1 This also illustrates how social positioning is firmly embedded in a dynamical (and high-dimensional) space of behaviours, which poses its own challenges. We will discuss these challenges later (Chapter 4).

wide range of studies, most of which focused on different factors that could influence the appropriateness of different social positioning behaviour (Section 2.1.2). Based on these developments, more dynamic accounts of social positioning were developed and investigated (Section 2.1.3) for which various social feedback cues play a role (Section 2.1.4). We will wrap up by further discussing this transition from relatively static accounts of social positioning to social positioning as a part of a rich interaction dynamic (Section 2.1.5).

2.1.1 *Describing social positions*

One of the earlier attempts to capture social positioning behaviours in humans is the study of **proxemics**. The term was coined by Hall [31], a sociologist, mixing observations of various territorial behaviours in animals, and cultural differences in social distancing behaviour. At the core of his theory are different zones of interpersonal distances; intimate space, personal space, social space, and public space. Each of these zones is defined as a range of interpersonal distances, and as such related to different perceptual qualities. For example, when interacting with someone in the intimate space zone (45-120cm) you can smell them, feel their warmth and easily touch them. When interacting with someone at the social space zone (120-365cm), touching is no longer possible and the focus goes to auditive and visual cues.

Besides distance, which is the focus of proxemics, orientation can also play an important role in social positioning. F-formations, as introduced by Kendon [49], describe the different spatial arrangements people can use in social interactions[2]. At the core of the theory is the definition of a circular shared space (o-space) to which all interactants have equal access. People can then be oriented in different ways around this space, e.g. side-to-side (next to each other), or face-to-face (facing each other).

As proxemics and F-formations would predict, many different social situations can be distinguished based on only position and orientation information (e.g. [29, 62]). As such, these models have provided a valuable, if somewhat unspecific, starting point for capturing parts of social positioning.

2.1.2 *Factors that influence social positioning*

There is a fascinating and varied set of studies into many different factors influencing social positioning, with a focus on proxemics. Consider for example the finding that female college students tended to prefer greater interaction distances when approached in dim light,

2 There is, of course, more work on spatial configurations, e.g. during walking [21]. We here focus on F-formations as it is the theory on orientations that is most prominently used in work on human-robot interaction (see Section 2.2.1)

and similarly tended to prefer greater interaction distances when approached more from behind [1]. Or the finding that whether someone is focused on themselves or on their social environment (also known as 'construal') also influences interpersonal closeness [39].

Much of the early work in this direction uses methods that deliberately focus on static measures, eliminating the dynamics of the interaction. One such method is the taking of photographs (e.g. [35][3]). Another common method is the use of projective measures, e.g. asking participants to place miniatures at 'appropriate' distances to each other (e.g. [105]). Lastly, many studies used a stop-task, where participants are approached slowly and asked to say stop when the approaching agent reaches an 'appropriate' distance (e.g. [1]).

In his extensive 1987 review [2], Aiello gives a much more extensive overview of most of the topics we touched upon in this section. This review also includes several tables summarizing *hundreds* of studies into the effects of various factors on social positioning. In these tables, these factors are roughly organized in five categories; (1) gender, culture and subculture; (2) personality and psychological disorders; (3) relationship; (4) situation; and (5) environment. If anything, these tables demonstrate that a great many interacting variables all influence social positioning.

2.1.3 *Dynamics of social positioning behaviours*

The extensive research into factors influencing social positioning has also given rise to several more dynamic accounts of social positioning, as also discussed by Aiello in his review [2]. In said review, he distinguishes between (1.) the protective function of personal space, capitalizing on "the consequences of inappropriately close spacing" [2, p. 393], and (2.) the communicative function of social positioning, capitalizing on distance as "a milieu within which a variety of behaviours and phenomena occur" [2, p. 391]. He then argues that, especially in the sense of this communicative function, one should not focus on considering personal space as a static bubble, but rather as one factor in the interaction between two people.

The intimacy equilibrium model [5] is one such dynamic account of social positioning. It poses that people within an interaction have a desired level of intimacy, balancing on an equilibrium between approach and avoid, and that they show compensatory behaviours when the actual perceived intimacy deviates from the desired level. The original model lists only a few specific compensatory behaviours, including adapting the interaction distance (a.o. discussed in the review

3 This study, conducted in 1972, describes two experimenters venturing out into the city, one of them secretly taking pictures while the other is trying to get a measuring standard in the picture by standing "alongside the interacting dyad holding a clipboard of known size without attracting attention." [35, p.493].

by Hayduk [33]), and avoiding eye contact [5, 30]. Various other compensatory behaviours fit the model, such as leaning away [65] and particular facial expressions [16]. According to the model, if the compensatory behaviours are not sufficient to achieve equilibrium, this is experienced as discomfort. The model has been extended in various ways, e.g. by assuming that a sufficiently large deviation from equilibrium will cause people to disengage from the interaction [3], but also by investigating how we can model the different reciprocating and averting compensatory behaviours that are used [4].

In this way, intimacy equilibrium treats social positioning as just one possible compensatory behaviour that can be used in an interaction. As such, it suggests that people can be comfortable in situations where they can not move further away from people, as long as they can show other compensatory behaviours such as gaze aversion. To turn this around, the presence of such compensatory behaviours may well signal a violation of the intimacy equilibrium.

2.1.4 *Social feedback cues*

Given the treatment of social positioning in humans as communicative, it is not surprising that there are various papers investigating which social feedback cues people give in such interactions. For example, the work of Patterson, Mullens, and Romano [73] identified various response behaviours that became more frequent as an experimenter came closer to people they did not know in a library, from blocking responses and leaning (away), to even getting up and leaving. Similarly, Mehrabian [70] found that differences in posture can reflect one's relationship with an (imagined) interaction partner. The review by Cappella [18] discusses similar, and many other, social feedback cues provided in a range of interactions between humans.

2.1.5 *Conclusions*

The early studies that we found focused more on static snapshots of social positioning, trying to find the right position and the way such positions were influenced by a variety of factors. This focus is also evident from many of the used methods, which ranged from literal snapshots to asking people to say 'stop' when they felt the person approaching them was getting uncomfortably close. These early studies found a broad, extensive, and diverse range of factors that could play a role. In fact, given the very large number of such identified factors, and the many more relevant factors that might not have been identified yet, this poses an important practical problem; how to correctly model these factors jointly? Or perhaps even more challenging, how to evaluate all these factors jointly? And will it be possible for anyone to properly consider all these factors in any interaction, given that some of them are very much internal? To our knowledge there exists no static account of social positioning that handles these practical limitations – and as we will argue in Chapter 4, such an account may well be impossible.

More recent work focused more on interaction dynamics, and the role that social positioning could play in such dynamics. As such, it often considers social positioning as a (communicative) aspect embedded in a social interaction. This is also reflected in the studies we discussed which specifically investigated the different non-verbal responses people use as part of, and in response to, social positioning.

Overall, we feel that the work on social positioning in humans has gone through an important transition; from social position*s* to social position*ing*.

2.2 SOCIAL POSITIONING IN HUMAN-ROBOT INTERACTION

We have defined social robots by their capacity to move, and to deliberately interact with humans through that movement. Positioning is a highly functional movement, and, as we have seen above, also one that plays an important role in social interaction. Consequently, there are many mobile social robots, with diverse functionality, and a range of different ways in which the positioning is used.

While a complete overview is out of scope, we do want to give some examples of the different kinds of mobile social robots. One way to organize them, is by means of locomotion – which can roughly be divided into wheel/track-based methods (e.g. Pepper, Roomba, Ollie, Wall-E) and leg-based methods (e.g. Nao, Asimo, Terminator). Alternatively, they can be organized by their intended purpose – such as guide robots (e.g. FROG, SPENCER, Robovie), service and healthcare robots (e.g. Baymax, Mobina, Care-O-Bot), or supporting social interactions[4]. The last means of organizing them that we will mention, is by their intended user group – be it children that have to learn to collaborate (e.g. SQUIRREL), or elderly that want to live independently as long as they can (e.g. ACCOMPANY).

A specific type of mobile social robot that is of particular relevance to this thesis, is the mobile robotic presence system (**MRP**). They have been defined by Kristoffersson [55] as a video-conferencing system mounted on a mobile robotic base. As such, they allow a remote user to connect and converse with people through the robot. Application areas include the office, to support remote working (e.g. [63, 89, 95]); schools, to support participation of hospital-bound children (e.g. [20, 27]); and the homes of elderly, to support visits by caregivers and family (e.g. [7, 12, 56]) or participation in activities (e.g. [96],

4 While there are robots aimed at supporting social interactions, such as the PARO, the only *mobile* social robots we could find that explicitly had that purpose we could find were all mobile robotic presence systems.

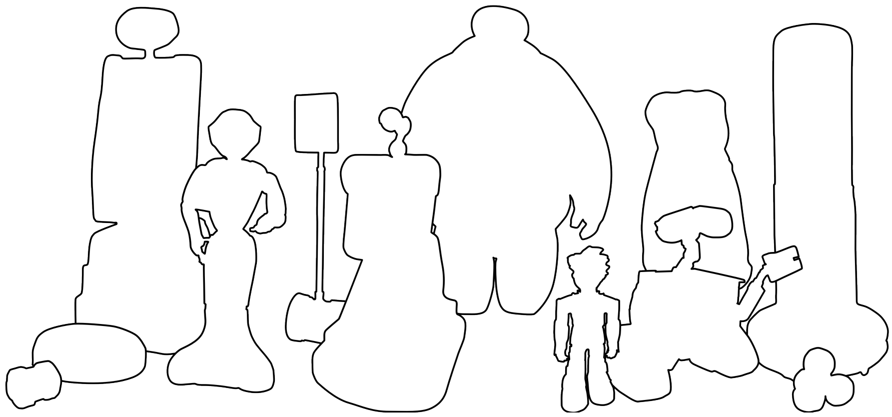


Figure 2: There exists a very wide range of mobile social robots, in terms of shape, size, locomotion, purpose, and intended user group. This illustration shows the shape and size of some of the social robots mentioned in this chapter – from the 16cm tall Dash to the 175cm tall TERESA.

TERESA). While MRPs are fully manually controlled in most cases, recently various efforts have started to implement autonomous and semi-autonomous behaviours (e.g. [50, 51, 77, 92], TERESA).

Where in human social positioning the focus has been on observing and modelling existing behaviour, in social robotics, social positioning is something that is being *developed*. This means that the pragmatism of finding an approach that works well enough can play a big role. It also means that there are often many other factors – design, robot appearance, robot size, and context – that could influence social positioning and that are developed in parallel.

For convenience, we will roughly distinguish four overlapping kinds of interaction phases for which social positioning is being developed within the field of social robotics. **Navigation** is moving around towards a location, and as such has a strong functional aspect to it. Still, there can be many social aspects in navigation, such as navigating around or side-by-side with people. More close-up social interactions often start with an **approach**, which can be seen as the social positioning behaviours required to initiate such a close-up social interaction. Its opposite, **retreat**, consists of the social positioning behaviours that are used to disengage from such a close-up social interaction. We will refer to the phase in between approach and retreat, and all the associated positioning behaviours, as **converse**.[5]

5 It is worth noting that these four terms were chosen to reflect with the most common behaviours during each of the phases. In theory it is possible to have a converse phase without any conversation. To roughly abstract away from specific social positioning behaviours, approach can be seen as a specific case of *engaging*, retreat as a specific case of *disengaging*, and converse as a specific case of *being engaged*. That said, we deliberately chose not to use those more abstract terms for the phases, as they are inherently harder to objectively separate – e.g. one could measure the end

We will in this section first discuss work that focused on social positions and distances a robot could use (Section 2.2.1). This work mostly treats social positioning as a static set of constants that a robot could use, mostly in navigation and approach. More recently, people have been moving towards developing a more dynamical social positioning (Section 2.2.2), which bears similarity to the developments within the field of human social positioning (Section 2.2.3).

2.2.1 *Social positions for robots*

There is a reasonable body of work investigating social positions for robots, often with a strong focus on proxemics, in particular on the personal space zones, and F-formations.

In social positioning for navigation the dominant approach is to try to navigate such that the robot never gets closer to people than certain set distances – these distances being derived from Hall's personal space zones [58] and/or other descriptions of the space people use [79]. This approach, while pragmatic and relatively effective, does pose some challenges. For example, how should we balance avoiding such intrusions against deviating from the shortest path [59], and how should we weigh multiple intrusions against each other [61]? Another complication with this approach, is that people often respond to the behaviour of the robot - which has led developers to look into the legibility of their navigation behaviour [64], and into ways in which these response behaviours can actually be used to further the navigation [57, 59].

Proxemics, in combination with F-formations, has similarly been used in studies investigating social positioning for approach. For example, Brandl, Mertens, and Schlick [13] have used the stop-task we also saw in studies on human positioning behaviour, and found effects of habituation, participant body position, robot speed and robot speed profile. Similarly, significant effects have been found in various settings; in different contexts [93], with different properties of the robot [104], with relation to the background of the participants [91], and for different cultures [43]. These findings show that taking proxemics and F-formations into account can have a positive effect on the perceived appropriateness of the displayed robot behaviour.

Social positioning for approach has also been approached by having participants control the robot remotely. In addition to this use of tele-operation, this approach often involves more extensive telepresence by using robots that are equipped with a video connection – i.e. MRPs – as well. The approach can be used to have participants experience the possibilities and limitations of the robot [7] or to inform design decisions [44]. The research of Kristoffersson et al. [56] and

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of an approaching movement, but there is no objective measure for when 'engaging' is complete.

van Oosterhout & Visser [72] actively observed the displayed behaviours. Both used manual annotations of visual data (video/photo), to investigate relevant patterns in the behaviour. Van Oosterhout & Visser [72] found that people generally position themselves within Hall's personal space zone. Kristoffersson et al. [56] found that when talking through a telepresence robot about a disembodied topic (here a remote control) participants tend to assume a L-shape arrangement, as Kendon's F-formations would predict [49]. Actively observing the behaviours used by participants controlling a robot thus seems a fruitful approach to investigate suitable social positioning of (telepresence) robots.

As in human-human interaction, these models thus too have provided, in general, a starting point for capturing and implementing parts of social positioning.

2.2.2 *Towards dynamic social positioning for artificial agents*

One factor that makes it hard to study human-robot interaction is that it is a dynamic process. Or, as Hüttenrauch et al. [41] put it when investigating the applicability of proxemics and F-formations to the field of robotics;

> The dynamic changes and transitions from one interaction episode state into the another one are difficult to express in terms of Hall's interpersonal distances and Kendon's F-formations arrangements when tried in a HRI scenario. [41, p. 5058]

On a basic level, considering human-robot interaction as a dynamic process means acknowledging that various aspects of an interaction can on their own change over time. Interaction takes time, actions of the robot take time to complete, and over time the needs and wants of an individual can change. These are the temporal dynamics of an interaction. There is a limited set of papers that explicitly look into these temporal dynamics of social positioning for interactions between people and a robot [37, 41, 56, 66].

But, beyond acknowledging change due to the progress of time, the dynamics of change can also be caused by the (social) interaction itself. These are the social dynamics of an interaction. That is, people could adapt to a robot and other people, and they could expect adaptive behaviours in return (see, for an example with a virtual agent, Box 2). Complex as they are, these dynamics allow for many interesting applications. For example, by relying on people to get out of the way of a navigating robot [57], to communicate that someone is deliberately being approached by a robot [83], to have virtual agents signal their approachability [76], or to influence the formation of people interacting with a robot [60]. As evidenced by this related work, the social dynamics, as well as the temporal dynamics, can have a strong influence on what happens in the interaction.

A specific application of these social dynamics, that befits the context of this thesis, is artificial agents deliberately using social feedback cues to influence the dynamics of social positioning – but we only found few examples of this in the literature. The focus here is mostly on situations where the robot provides cues, rather than being responsive to them itself. Recent work found that robots can effectively signal their (perceptual) needs to influence the proxemic preferences of people with which they are interacting [67]. Using a virtual agent instead of a physical robot, Kastanis and Slater [48] have also investigated ways to influence the proxemic preferences of people; they trained an agent to position itself such as to most effectively cause participants to move to a particular position in a space.

When we look beyond social positioning there are several more examples to be found of robots using social feedback cues to try and improve the interaction. Previous work has used easy to detect cues, e.g. the use of estimated subjective task difficulty to try and adapt the difficulty of a learning task [84], and the use of specific non-verbal utterances to guide the adaptive behaviours of a conversational agent [17]. Work by Jung et al. investigated human-robot teamwork and found that when their robots used back-channeling, this improved team functioning, though it also decreased perceived competence [46]. Hoffman et al. found that a robot that provided a range of acknowledging behaviours[6] could influence self-disclosure [38]. And Brule et al. investigated the effects of a robot signalling trustworthiness on its interactions [15].

Together, this body of work suggests that robots can, indeed, participate in the social dynamic – or at least, that they can provide social feedback cues in a way that is picked up by humans.

2.2.3 *Conclusions*

Similar to the studies we found on social positioning in human-human interaction, in human-robot interaction there too has been a transition from static snapshots of social positions to more dynamic uses of social positioning behaviours. Already in the early studies we saw various ways in which such 'static' behaviour of the robot did not fit well within the interaction – mostly because people would often respond to the behaviour of the robot. In other words, there are va-

6 Interestingly, Hoffman et al. refer to these behaviours as 'responsiveness'. They used a range of behaviours that would intuitively fit into responsiveness as used in this thesis; focus towards the human, animacy conveyed through a gentle sway, and affirmative nods in response to speech (inverted for low responsiveness behaviour). Their use of responsiveness is, at the same time, somewhat different, as it does not place the same emphasis on using and responding to social feedback cues that will be at the core of our definition of 'responsiveness'.

Intimacy regulation in interactions with virtual agents

Beyond robots, there is another class of artificial agents that might benefit from suitable social positioning behaviours; virtual agents in immersive virtual environments. A first question is if theories on social positioning behaviours carry over to such interactions. But, in addition, since such environments are completely controlled, they also allow for a controlled experiment into the interactions that play a role in social positioning.

These ideas were picked up by one of our Master students, Jan Kolkmeijer, who specifically looked at equilibrium theory; the idea that people try to balance the intimacy of an interaction by changing their gaze and positioning behaviours [5]. For example, if someone we don't know sits very close to us on the bus, we might 'compensate' by avoiding eye contact. In his work, he conducted a study in which participants (n=35) would witness an argument over the guilt of a suspect between two agents, one agent occasionally displaying high intimacy behaviours, getting close and/or gazing intensely, the other agent low intimacy behaviours, going further away and/or averting gaze.

He found that both distance and gaze have an effect on the reactions of participants – in some cases even jointly. This does suggest that equilibrium theory also holds for virtual agents in immersive virtual environments. It also illustrates how social positioning is, indeed, a dynamic back-and-forth, where the actions of one (virtual) agent can lead to clear and meaningful (re)actions of another (human) agent.

Box 2: Interacting with virtual agents in shared space: Single and joint effects of gaze and proxemics. This work has been conducted by Jan Kolkmeier as part of his master's thesis [53], whom I had the pleasure of supervising in the process. It has previously been published at IVA 2016 [54].

rious temporal and social dynamics at play that should ideally be considered.

Furthermore, we found various robot behaviours that were actively designed to make use of the dynamic behaviours of people – from signalling proxemic needs and trustworthiness, to using peoples non-verbal utterances to guide the adaptive behaviour of a conversational agent.

Overall, we feel that while static theories on social positioning have provided a good starting point for social positioning in human-robot interaction, there also is an active and necessary development towards approaches that more and more acknowledge and use the dynamics inherent in interaction.

2.3 USING THE INTERACTION AS THE SOLUTION

Responsiveness does not exist as a general theory. Still, there is a variety of existing work in artificial agents that we feel aligns with our definition of the responsive approach. Our aim here is not to give a complete overview, but instead to illustrate how solutions fitting within the framework of a responsive approach exist and have been shown to be effective.

We do not intend to argue that responsiveness to feedback is novel; in fact, a variety of work on human-human and human-agent interaction can be interpreted as examples of it. We will here give a selection of these examples to provide a more concrete background for the approach. Giving a complete overview would be infeasible since a broader interpretation of responsiveness may well be applicable to most types of interaction; rather, we intend to illustrate how solutions fitting within the framework of a responsive approach have been shown to exist and be effective.

> If Person A increases proximity, decreases gaze, is verbally revealing, and poses an intimate question in a loud voice and rapid speech, can the listener's response pattern be predicted? The answer must be negative. [18, p.125]

This is one of the conclusions from Cappella's 1981 review of mutual influence in expressive behaviour [18]. Though he does not suggest a responsive approach as a way to handle this, the many non-verbal response behaviours he discusses may be well suited as feedback variables.

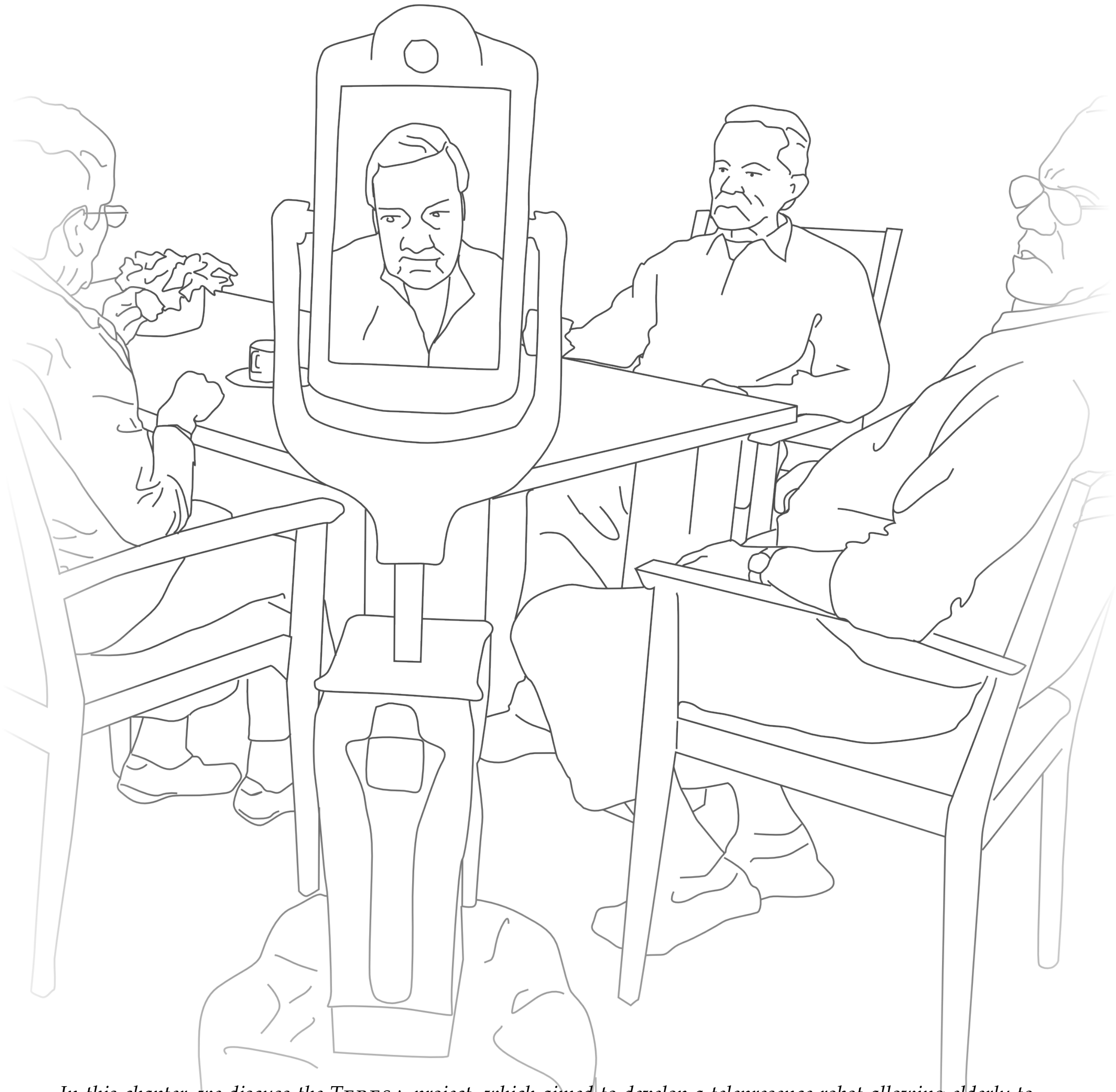
Similar findings on the relevance of such potential feedback variables can be found throughout the literature on human-human interaction. For example, in their 'tacit communication game', where participants had to use a restricted set of actions with shapes shown on a computer to communicate a goal configuration, de Ruiter *et al.* found that the simple feedback of seeing how ones communication partner responds to a message clearly helps improve task performance over time [25].

A responsive approach can also be found in the reasoning about common ground. In conversations, we often refer to shared knowledge, e.g. "that animal", "the thing I did yesterday". But how can we do so, such that we can be certain those definite references are correctly understood? When approached logically, this requires common ground; those involved in the conversation should all know the reference, know that they all know the reference, know that they all know that they all know the reference, and so on ad infinitum. In other words, when following this (setting-specific) approach, an infinite set of facts would be required to optimally make a definite reference – which would be rather infeasible in any real-life setting. One option, proposed by Clark & Marshall in 1981, after discussing this precise problem, is to try and make this approach more feasible by using a range of heuristics. But interestingly, over two decennia later in 2004, Pickering & Garrod proposed a responsive alternative, which roughly entailed simply assuming common ground ('implicit common ground') and following an improvement strategy if feedback indicates that this assumption was wrong.

Approaches akin to responsiveness have recently also been proposed to specific areas in human-robot interaction. There is the range of aforementioned work with robots either providing [15, 38, 46] or adapting to social feedback cues [17, 84]. But more directly in line is Jung's recent argument for emotion grounding *through* the interaction, which puts a strong emphasis on the role of responding to each other in interaction as a means of conveying emotion – as opposed to conveying emotion through one-sided expressions, facial or otherwise [45].

2.3.1 *Conclusions*

Together, these works show that the inner thoughts of others, be it common ground or emotional affect, might well be established through interaction. A recurring pattern is the transition from more static approaches (one-sided emotional expressions, a setting-specific approach to common ground) to this focus on the interaction. The work on social positioning in human-human and human-robot interaction has not yet fully gone through this interaction, but if the work discussed here is any indication, doing so might well make for an effective approach to finding the 'right' position.



In this chapter, we discuss the Teresa project, which aimed to develop a telepresence robot allowing elderly to join social activities if they cannot be present in person. Specifically, we describe the procedure and outcomes of three studies exploring the, often dynamic, behaviours used:

- *A contextual analysis into the positioning behaviours and social cues used by elderly during a range of social gatherings. Previously reported on as part of a Teresa deliverable [99].*
- *A data collection where we recorded the positioning data of a participant repeatedly approaching and retreating from a group of 3 peers with a telepresence robot to jointly solve a murder mystery, as well as subjective ratings of those behaviours from those peers. Previously published in [103].*
- *An evaluation in which a telepresence robot with semi-autonomous dynamic social positioning behaviours (Wizard-of-Oz) was used for several weeks during social gatherings in a nursing home for the elderly. Previously reported on as part of a Teresa deliverable [100].*

These studies give a broad insight in the context that forms the backdrop for this thesis; we saw specific challenges in detecting factors influencing social positioning, the need to avoid generalizing, and the opportunity to use various dynamic response behaviours. In other words, these observations are what inspired our idea of responsiveness as applied to the context of the Teresa project.

3 OBSERVING SOCIAL POSITIONING BEHAVIOURS IN CONTEXT

> Imagine sitting in a small apartment in a nursing home for the elderly. The air is clean, though it smells of disinfectant. If you look around, you recognize the furniture and trinkets you have collected in a lifetime. Still, you are not in the house where you have spend most of your life. There is so much that had to stay behind when you moved in. And yet, you have also gained things, for there is a caring staff and new friends made. You meet over coffee, over dinner, during bingo, or during any of the other activities that are organized in the common area. You discuss the news, grandchildren, and just enjoy each other's company. In fact, over in the common area, people are playing a pub quiz right now. But you did not join. Perhaps it is because of a broken hip restricting your movements, you may have a contagious sickness, or you may have just felt too tired.
>
> You are here, alone, in a small apartment in a nursing home for the elderly.

Context is essential for social robotics. It provides purpose to the deliberate interactions with humans that social robots engage in. Since social robots are being *developed*, a context is needed to direct that development. Specific to this thesis: Even though we can make abstract claims on the importance of dynamics in social positioning, as we did in the previous chapter, it is only when we observe these dynamics in a real environment that they get grounded.

The ideas on which this thesis is focused originate mainly in one specific context; the aforementioned TERESA project. The vision of the project was that an elderly person[1] who cannot attend a social activity in person, such as the scenario sketched above, can instead do so using a mobile robotic presence platform, an **MRP**. Within this context, the consortium developed various components to allow the MRP to do social positioning in a semi-autonomous way (see Box 3). The idea being that these semi-autonomous behaviours would help facilitate the social interactions; allowing the users to focus on

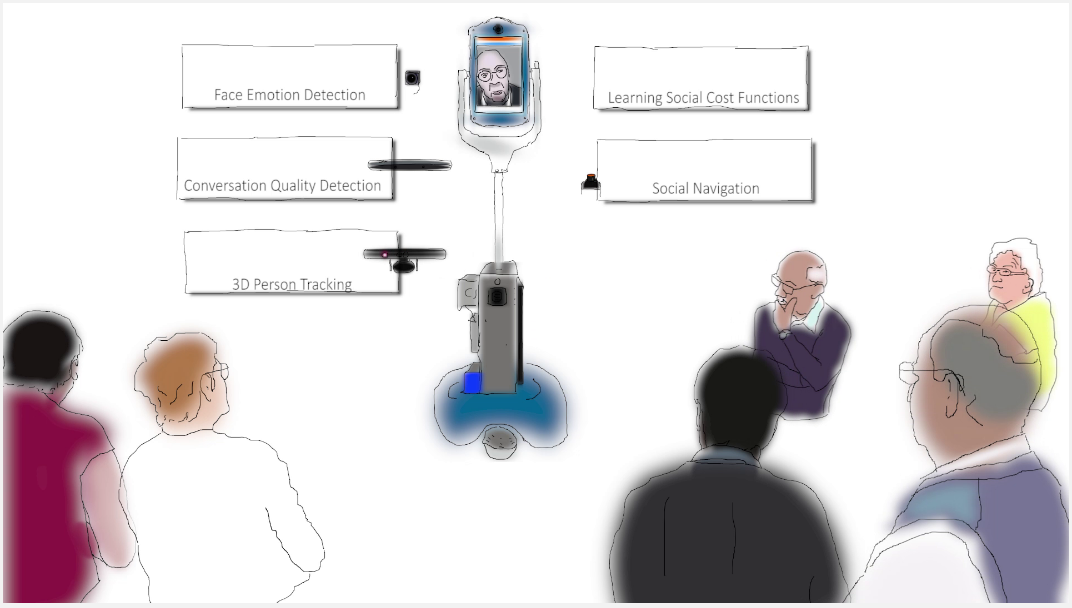
1 'Elderly' is a term that refers to a loosely defined user group with very diverse characteristics. We will in this chapter more specifically look at (primarily) Dutch residents in nursing homes for the elderly, that do not live fully independently. For convenience sake, we will continue using the term 'elderly' to refer to our user group.

Semi-autonomous telepresence robot behaviours to support social participation

TERESA is a telepresence robot that allows elderly to participate in social activities from a distance, if they cannot do so in person. The TERESA project was conducted by a consortium, supported by the European Community's Seventh Framework Programme (EU-FP7-611153). The aim of the project was to develop semi-autonomous socially intelligent behaviours for the robot, allowing the visitor to focus on their friends.

To develop the semi-autonomous social positioning, we combined various intelligent components developed by the consortium partners. This includes machine learning of behaviours for close-range interaction (University of Amsterdam, University of Oxford), autonomous social navigation (Universidad Pablo de Olavide), robot hardware (Giraff Technologies, IDmind), face emotion detection (Imperial College London), conversation quality and person/body posture detection (University of Twente), an interface (University of Twente), and sociological evaluations with our end users (MADoPA).

The work in this thesis has mostly been conducted within this project, with the primary aim of designing socially normative behaviours for TERESA. To achieve this aim, we have conducted a contextual analysis and a long-term study (discussed in Chapter 3). In addition to more practical recommendations to our partners directly derived from that work, this has also led to our ideas for responsiveness, as a method to find socially normative behaviours.



Box 3: TERESA: Telepresent Reinforcement-learning Social Agent

the conversation, instead of having to control the robot by providing low-level movement instructions. In this chapter we will focus on our investigation of socially normative social positioning within this context.

As the literature discussed in the previous chapter show, dynamics are likely to play a big role in these socially normative behaviours – but how does this work in this specific context? Where the theoretical background focused on more abstract problems, such as having (too) many different factors influencing proxemics, we will here explore the practical problems and opportunities specific to this setting; what factors play a role, can we detect them, what social cues do elderly provide, how do people adapt to each other, how do people adapt to robots?

In addition, this chapter looks into how our work could relate and be relevant to a specific real-world need, by actively grounding it in the context of TERESA and looking into the assumptions behind the project. More specifically, we will look into the assumptions that (1) there is a need to support the social interactions of elderly, (2) having an MRP (with semi-autonomous dynamic behaviours) mediate still allows for a mostly natural social interaction, and (3) manual control of an MRP is difficult for elderly and distracts from the interaction.

While context thus is essential, it is also directly at odds with the generalizability of ones work. On the one hand, grounding is deliberately specific to a context. On the other hand, and in contrast, generalizability is about drawing conclusions that are *not* specific to a context. This is a conflict which is, consequently, inherent to social robotics research. This will also become apparent throughout this chapter, as it is only through assumptions that we can separate our observations into those that can and cannot be generalized. Therefore, this chapter, deliberately, is written as a relatively free-form exploration of the context, while the others will be more restrained. Nonetheless, the context of TERESA of course permeates this whole thesis.

This chapter addresses a very broad question about the dynamics that play a role in a setting where a semi-autonomous MRP supports social interactions for elderly. While this is, partly, inherent to the exploratory nature of the work, we have approached this by splitting that question into three different studies, each with its own focus (see Table 2 for an overview). We started with observing the status quo, by conducting a contextual analysis of social interactions for elderly, and of elderly manually controlling an MRP in social interactions (Section 3.1). To get more detailed and controlled data on how people behave when an MRP is actively used to support social interaction, we then conducted a data collection and investigated the dynamics apparent in that data set – avoiding the challenges of manually controlling the MRP that we observed in elderly, by using students as our participants (3.2). The found dynamics were then explored furt-

	Context: TERESA	*a*	semi-autonomous	MRP	supporting	social interaction	for elderly
3.1	Contextual analysis	*of*				social interaction	for elderly
		and of		MRP			for elderly
3.2	Exploratory data-collection	*of*		MRP	supporting	social interaction	
3.3	Long-term evaluation	*of a*	semi-autonomous	MRP	supporting	social interaction	for elderly

Table 2: Outline of the chapter. To investigate our robot within context, we conducted three studies that focused on different aspects of that context. The contextual analysis and exploratory data-collection focused primarily on understanding the context, while the evaluation also looked at dynamic behaviours within that context.

her *with* members of the user group in an evaluation spanning several weekly sessions (Section 3.3). This last study is somewhat different from the earlier two in that it gave few new insights into the dynamics, but instead focused more on the social effects of using an MRP with several dynamic positioning behaviours.

In all, this combined work gave us a rich and exploratory insight into the relevant needs, requirements, and limitations, and allowed us to form more specific ideas about the kinds of dynamics that play a role in this context (Section 3.4).

3.1 CONTEXTUAL ANALYSIS

The work described in this section has previously been reported as part of a deliverable for TERESA*; [99].*

To get a better impression of our target group and the existing contexts in which the TERESA robot will be to navigate itself, we conducted various observations. Specifically, we investigated different kinds of social situations, the applicability of proxemics to elderly (in interaction and in navigation), and other social signals used by elderly. We focused our observations on social activities with various elderly in the same room, because those allowed us to study both one-on-one and group interactions. We also included observations on elderly using the TERESA robot to interact with their peers.

3.1.1 *Observation goals*

In order to gain an understanding of the social activities TERESA is intended to function in, we wanted to find out what were the prevalent social activities that the elderly at our data collection locations engage in. Also, we were interested to gain an understanding of the general flow of events and interactions during these social activities. This led to the following question:

1. What social activities do the observed elderly engage in predominantly, and what is the general sequence of events and interactions during these social activities?

Since our focus was on the development of (semi-autonomous) social positioning behaviour for TERESA, we further were interested in the social positioning behaviours we could observe. We split this into two questions. Firstly, as a practical condition, we wanted to investigate how much physical space would be available for the robot and the elderly to move around in during the observed social activities. Secondly, we wanted to investigate what different interaction distances elderly use during social activities, and what factors might be influencing the choice for particular interaction distances at particular moments:

2. How much physical space is available for (social) navigation during the observed social activities?

3. What interaction distances do the observed elderly use during social activities, and what factors might be influencing their choices for these interaction distances?

While the previous two questions cover the primary actions available to TERESA, we also wanted to learn more about the kind of social signals TERESA might be able to perceive and use, which lead to the following question:

4. Which social signals do elderly use to communicate their needs, and what is the apparent goal of these signals?

Because interacting through the robot may pose its own challenges to the target group, we further aimed to investigate such interactions. This was an exploratory first step; what went wrong, what was the effect on the users, how did the use of the robot influence the interactions? We will further and more rigorously extent this exploration in the following sections (Sections 3.2 and 3.3), but for now guided it with a broad question:

5. What are the challenges that arise when elderly control an MRP?

Together, these observations aimed to give further insights into the context in which TERESA is to function.

3.1.2 *Methods*

Since we are interested in two kinds of observations, we used two methods to study them. To investigate the first five observation goals, we observed a variety of social activities involving groups of elderly 'as they are'. To investigate the last observation goal, we observed members of the target group as they controlled and interacted with the TERESA robot during a TERESA data collection.

3.1.2.1 *Observing social activities*

To observe the social situations 'as they are', we performed passive observations. To this end, we created forms in which we could easily indicate the sequence of events and interactions during these social activities. The forms further allowed for indicating the navigation space available during those events and interactions, as well as for indicating the different kinds of social signals and the frequency of those social signals.

During our observations we openly sat down close to the observed social event and started taking notes on the forms. For organized events, we always discussed our procedure beforehand with the organizers. To minimize the influence of our presence, we did not introduce ourselves beforehand to the elderly, though we always explained our intent and purpose to anyone who had questions.

Observations were conducted at three locations; retirement home 'De Polbeek', 'het Alzheimercafé Oldenzaal', and 'de Ariënsstaete'. An overview of the different activities we observed and their attendance can be found in Table 3. All our observations here followed this same procedure.

DE POLBEEK 'De Polbeek' is a retirement home located in Zutphen, the Netherlands, providing care to clients with various cognitive and physical impairments, but who do not require constant care. Some of the elderly attending the activities are elderly living independently in the neighbourhood, others live in assisted living. Central in the retirement home is a big common area, which is open all day. It provides ample place to sit around tables and is used for most social events, both organized and spontaneous. A central counter in front of the kitchen serves as a combined reception, café, and shop. Around noon a meal is served, primarily to elderly that eat there every day. Small snacks are served all day long. The common area is mainly used by elderly regulars. Two smaller 'living rooms' in a more private location provide day care to two groups of elderly with cognitive impairments (mostly dementia). On the 15th of May 2014 one observer spend the day in both the common area and one of the 'living rooms' to carry out the research.

HET ALZHEIMERCAFÉ OLDENZAAL 'Het Alzheimercafé Oldenzaal' is a monthly meeting in Oldenzaal, the Netherlands, on the various practical and emotional concerns that come with Alzheimer and dementia in general. It is open to anyone who wants to attend, but mainly attended by elderly with some form of dementia and their caregivers. Commonly, meetings are attended by 40 to 50 people. The observed meeting was a celebration of the 10 year anniversary, attended by about 100 people. Main speaker was the Dutch singer Marga Bult, who performed some sentimental songs clearly well-known to the attendees, as many sang along. On the 26th of June 2014 one observer made observations during this meeting.

DE ARIËNSSTAETE 'De Ariënsstaete' is a retirement home, located in Enschede, the Netherlands, that is similar to the Polbeek, but slightly larger. Though it also has a central common area, we did our observations in an open meeting space at one of the far ends of the building. On the 17th of July 2014 one observer conducted the data collection during a memory training session, in which six elderly (all female) performed various activities to improve their memory.

3.1.2.2 *Observing interactions with the Giraff robot*

In addition to the observations described above, we also did observations of various elderly while they were controlling the TERESA telepresence robot. More specifically, we used the Giraff robot for this – which was a commercially available MRP platform, on which we later mounted additional sensors and a new shell to create the TERESA robot. For practical and safety reasons, the observations we conducted here were more controlled and happened under the supervision of one or more experimenters. These observations were aimed at exploring the variety of challenges that using the robot could present to our target group.

To conduct this exploration, we first conducted informal observations at two occasions. The first was in the Living lab in Troyes, France, during the first integration week for the TERESA project. On the 8th of July we had several people control TERESA, among which one member of the target group. In the second informal observation, three members of the target group likewise controlled TERESA.

During a later data collection for the TERESA project, we further investigated similar situations where elderly controlled the robot. From September 8th to September 15th and from October 14th to October 17th, a total of 9 members of the target group participated. All these participants used the TERESA robot to interact with one or two of their peers, making for a total of 19 participants. In these interactions, we investigated both situations in which the participating elderly controlled the robot themselves and situations in which a confederate controlled the robot. As part of our explorations, the confederate was instructed to display both 'good' and 'bad' autonomous behaviour.

3.1.3 *Findings*

We will here discuss our findings, organizing them by our observation goals. Implications that these findings could have for the design of socially normative semi-autonomous behaviour for telepresence robots will be discussed in the conclusions and discussion section.

3.1.3.1 *What social activities do the observed elderly engage in predominantly, and what is the general sequence of events and interactions during these social activities?*

In Table 3 we have listed the various social events during which we have done our observations. The activities that followed a fixed schedule or were guided by the organizer in general all had roughly the same schedule; arrival, welcome/introduction, go through the steps of the activity, departure. There usually was a notably large time window for both arrival and departure (15-30 minutes). Within this time window, people would slowly arrive/depart – with some of them being helped in this by caregivers – and strike up small conversations

3.1.3.2 *How much physical space is available for (social) navigation during the observed social activities?*

We observed that people actively tried to keep open a lot of physical space free of obstacles, presumably to ease navigation. For example, during the shared meal several caregivers and elderly without walking problems actively cleared away all walking aids from the main paths (and returned them to their owners at the end of the meal). Though the space was a bit more cramped at the Alzheimer café, we there observed similar behaviour.

Activity	Attendants	Duration	Structure
Shared dinner in the restaurant	40 elderly	12-13h	Scheduled
Spending time in a shared living room	5-3 elderly	Ongoing	Free
Participating in a social art project (Table of Memories)	5 elderly	14-16h	Guided by organizer
Sitting together in the café	6 elderly	Ongoing	Free
Attending a meeting with live music (Alzheimer café)	~100 elderly and caregivers	19-22h	Guided by organizer and main speaker
Participating in memory training	6 elderly	1h 30m	Guided by organizer

Table 3: Overview of the observed social events. The last column indicates the extent to which the participants had to follow a fixed schedule.

3.1.3.3 *What interaction distances do the observed elderly use during social activities, and what factors might be influencing their choices for these interaction distances?*

Only a part of the observed population maintained a typical[2] distance of about 1-1.5m to their communication partners. We also commonly observed that people were closer to each other than that while communicating.

Among people with hearing problems (identifiable by their hearing aids and remarks they made to signal their hearing problems), 'leaning' behaviour was very commonly observed. During conversation, the person with hearing problems would (1.) turn upper body and face towards the person they were talking with, and (2.) lean their upper body towards their conversation partner. A small subset would also turn their head, presumably to aim their 'good ear' at their conversation partner. The conversation partner commonly returned the leaning behaviour. We observed several times that a conversation partner relayed to the person sitting directly next to them what others in a group had said. In most cases, the 'leaning' behaviour was only used during conversation and the interacting parties kept more distance when not talking. In one case we saw someone displaying this 'leaning' behaviour towards an interaction partner some meters away at

2 In line with what one would expect based on the static models of interaction distances discussed in the previous chapter.

the far end of a table – which suggests that it is also used as a social signal.

We observed one exception; an older lady who had severe hearing problems did not display any leaning behaviour. One of the caregivers compensated for this by moving real close and showing strong leaning behaviours. In this particular case it took the observer well over 30 minutes to realize that the older lady had severe hearing problems, which suggests that the leaning behaviour in interactions also provides an important social cue.

In interactions between standing and sitting people, the standing people often used the chairs of the sitting people for support. This use of chairs for support also occurred when no conversation took place. When conversation between someone standing and someone sitting did take place, the standing people commonly leant over the sitting people to establish eye contact. As a result, people were very close to each other in these interactions. Possibly this behaviour is also intended to compensate for hearing problems, as it was commonly observed in interactions where one of the interaction partners seemed to have hearing problems.

Some of the caregivers also got very close to their interaction partners. For example, we often saw caregivers crouch to be on the same height as the sitting people they were interacting with. These behaviours may have partly been for practical reasons, such as hearing problems. However, since they were also displayed in communication with people without hearing problems, such as the observer, it is likely that these behaviours are also used as a social signal – presumably to signal social closeness through physical closeness. These behaviours were observed more in caregivers who guide social activities[3], than in caregivers who do more physical work, such as distributing medication, helping people stand up, and cleaning.

The few people we observed who were severely restricted in their freedom of movement and used a wheelchair, all did not seem to interact much with the people in their environment. They also seemed to be at a somewhat larger distance from the people they were in groups with than commonly observed.

3.1.3.4 *Which social signals do elderly use to communicate their needs, and what is the apparent goal of these signals?*

Some of the observed elderly use large gestures; for example, during the meal, when one group wanted to ask for an extra serving, the

3 In the Netherlands, where we did our observations, there is a function in nursing homes for the elderly dedicated to providing meaningful (social) activities to the inhabitants. People with this function – 'Activiteitenbegeleiders' – organize and guide these (social) activities, often with the help of volunteers that they supervise. Most of the social activities being organized fall under their responsibility, from memory training to the shared living room.

whole group started gesturing wildly (including partly standing up) to get the attention of the waiter. Another example is that of an older lady, who became a little angry and in expressing that started leaning and pointing towards the person she was angry at.

While the observed elderly were navigating, we saw them use surprisingly little social signals; most of the (potential) 'conflicts' were very effectively resolved by either waiting, forming a line or choosing another direction altogether. This should not be taken to suggest that navigation was not social, but rather that, as far as we observed, there were few explicit gestures involved.

Waiting as a strategy to resolve navigation conflicts has also been found effective for social robots [59].

3.1.3.5 *What are the challenges that arise when elderly use* TERESA*?*

Before they could drive the robot with minimal assistance, the observed elderly required 20-60 minutes training. These longer times for training seemed to be partly caused by a lack of experience with computers in general, since those that required shorter training usually report being more familiar with computers. After training, they often drove slow and carefully (with some exceptions). One of our participants had polyarthritis, causing additional difficulties in using her hands to control the robot.

The conversations were strongly influenced by being mediated by a telepresence robot. Many of the elderly were concentrating strongly on controlling the robot and as a result seemed to be less available for conversation. Or, as one participant remarked; "I can't do everything at the same time". One of the participants even made a similar remark while not he, but the confederate was controlling the robot.

Though this may well have been a novelty effect, much of the conversation was about the robot. In addition, some of those interacting with the robot tended to give it orders (such as "follow me", "sit down"). They do however seem to feel presence; some even remarked that they saw no difference between conversations mediated by the robot and conversations in person, describing it as much more 'present' than talking through a phone or Skype.

Afterwards, many of the participants clearly indicated that they enjoyed the experience. Despite the confederate also displaying 'bad' behaviours, some of them still indicated that they liked the autonomous behaviour of the robot. As one participant remarked; "It is my husband that I don't trust [to control the robot], not the robot!"

3.1.3.6 *Which other signals and factors could be relevant for social behaviour with elderly?*

Some of our observations did not really fit the other observation goals, but could still be relevant for social behaviour with elderly. We have here listed the most salient;

- The great majority of interactions took place between sitting elderly. Interactions between standing elderly were uncommon, interactions between moving elderly even more so.
- Some elderly did not participate pro-actively in conversations and other interactions; they did react when spoken to, but did not really take initiative. We observed this behaviour more often in the 'living room' and during the Alzheimer café, which suggests it may be related to dementia.
- Many elderly seemed to have a select group of contacts, even in a bigger crowd. Their interaction mostly seemed to be limited to people in this group, though caregivers sometimes interjected.
- Most of the observed elderly seemed to enjoy their social interactions.

3.1.4 *Conclusions and Discussion*

We have observed a variety of different social activities in which the TERESA robot could play a role, from organized activities with live performances to just a shared coffee among friends. Our observations have a range of implications that are specific to the design of the TERESA robot and its (socially normative behaviours (see Table 4 for an overview).

Beyond that, and more generally applicable, our findings indicate that our target group is complex; various internal, highly personal, variables strongly influence their behaviour in interactions. One of the limitations of the generalized conclusions above is that they focus on the majority, without taking these individual differences into account. Examples include the one person we observed with hearing problems that did not show leaning behaviour, for which a caregiver compensated by showing strong leaning behaviours towards her, and the person whose polyarthritis hindered her ability to control the robot. It would thus be interesting and relevant to try and take these individual differences into account.

Overall, these observations suggest that – within this context – numerous factors exist that influence social positioning. The observed people seem to not only use a static default distance, but also adapt their position as part of the interaction in their own individual ways. We saw such adaptations for practical reasons, e.g. to get support from the chair someone is sitting on, or to reduce hearing problems. And we also saw such adaptations in other situations, e.g. the caregivers getting close to their interaction partners.

Type	Findings
Physical space	• The TERESA robot will probably not have to navigate in cluttered locations, since most areas in which elderly interact are actively kept free of obstacles.
Interaction distances	• As Hall's work on proxemics would predict [31], elderly to some extent respect each other's personal zones. However, elderly with hearing problems commonly use 'leaning behaviour' where those involved in an interaction actively lean in to intimate distances, presumably to hear each other better. This finding is consistent with those of Webb & Weber [105], and rather relevant given the prevalence of Presbycusis (age related hearing loss) – which affects over half of the population aged 75 and above [10]. The TERESA robot will probably have to take this into account as a requirement, even though the capacity to change the volume settings provides alternative ways of handling these situations.
	• Caregivers often get very close to their interaction partners, also those without hearing problems. This suggests that it is a social signal (probably indicating social closeness), which could also be used by the TERESA robot.
Social signals	• Though some elderly use rather large gestures in communication, we saw few explicit gestures in navigating. Potential conflicts in navigating are often effectively resolved by either waiting, forming a line or choosing another direction altogether. The TERESA robot should probably incorporate these or similar strategies.
Manual control	• Controlling the robot is hard to learn for our elderly participants, and even after training requires a lot of effort, reducing the quality of the conversation. Introducing semi-autonomous navigation, as the TERESA project aims to do, thus could well help make the robot more usable for this user group.

Table 4: Overview of some of the key findings of our contextual analysis and their implication for the TERESA robot.

3.2 INTERACTIONS WITH A TELEPRESENCE ROBOT; AN EXPLORATORY DATA COLLECTION

The work described in this section has previously been published as; [103].

The contextual analysis gave us rich insights in the social interactions between elderly, and in what happens when elderly control an MRP – but we did not see rich interactions between the MRP and people. This means there is an important question still open; what social positioning dynamics happen in interactions between people and TERESA? Are these dynamics similar to what we observed in human-human interaction, or do new dynamics arise?

To truly investigate the dynamic back-and-forth, of interaction, the robot should actively partake; fortunately, in the case of an MRP we can achieve this by having participants control the MRP. That way, by using different participants to control the robot in interactions with different groups, different dynamics can arise and be observed. A limitation of this approach is that the quality of these dynamics will likely be influenced by how well the participants can control the MRP. Thus, ideally we would use participants who have sufficiently good control over the robot; since we found in the previous section that elderly have difficulty controlling the robot, we thus opted to instead do this study with students – which also had the practical advantage of being easier to arrange. In addition, we actively collected data on how the behaviours were perceived, allowing us to not only look at the frequency of particular dynamics, but also at their perceived quality.

This allowed us to set up a study in which we observed the dynamics of both humans and the (human-controlled) MRP at the same time. In this study, one participant (the **Visitor**) controlled the MRP to approach a group of three other participants (the **Interaction Targets**) to have a brief conversation with them, after which they would retreat with the robot (Figure 3). To collect more data, we set up a task that required the Visitor to conduct multiple such approach/converse/retreat-cycles in each session. Participants could use any social positioning behaviour they found suitable, to allow for the interaction dynamics to arise.

We approached these observations in two steps, with as the first step an extensive data collection. We used a tracking system to track each participant in the interaction and get detailed information on their positioning behaviour. This also allowed us to look at the non-verbal reactions of the Interaction Targets to the behaviours of the Visitor. In addition, we used questionnaires after each approach/converse/retreat to collect subjective data on how the participants perceived the dynamics of the interaction.

Our second step was an inductive analysis of our data, trying to find patterns in what is perceived as appropriate behaviour. This methodology was aimed at generating hypotheses on (dynamic) features that could be taken into account when designing social positioning (telepresence) robot behaviour for conversation with a group. Therefore, we applied inductive reasoning to go from patterns that can be qualitatively and quantitatively observed in the collected data to hypotheses for more general situations.

This section reports on our application of this inductive methodology, resulting in various hypotheses on social positioning in a dynamic interaction between a (telepresence) robot and a group. To do so, we will specify our method in details (Section 3.2.1), present our findings (Section 3.2.2), and discuss the implications and limitations of those findings (Section 3.2.3).

3.2.1 *Method*

The aim of this study was to collect data that can be used to generate hypotheses on (dynamic) features that could be taken into account when designing social positioning robot behaviour for interaction with a small group. To achieve this, we created a setting in which groups of four people would go through several cycles of approach/converse/retreat behaviour. One of the participants was present through a telepresence robot (the **Visitor**), and used the robot to interact with the rest of the group (the **Interaction Targets**).

One of the challenges to our aim was that to allow for the dynamics to arise we wanted to leave our participants as free as possible. At the same time, we wanted to keep the different cycles comparable, to make the comparison of the acquired quantitative data easier. Therefore, we created a somewhat controlled setting where we 'reset' the position of the Interaction Targets *between* the cycles, while allowing them to move freely *during* the cycles.

Another challenge was to automatically generate robot behaviours that are sufficiently dynamic and appropriate. We have here resolved this by having one participant control the telepresence robot used in the study.

3.2.1.1 *Task*

The task had to motivate the participants to have a conversation in which the Visitor had to go through several cycles of approach/converse/retreat behaviour. We thus asked our participants to solve a murder mystery, where the Visitor had to go and collect eight clues, and return to the group in order to share the clues. To eliminate effects of the specifics of the murder mystery, groups were randomly assigned to one of three murder mysteries. Preliminary analysis did not indicate any effect of the different murder mysteries, so this variable has been excluded from the analysis.

The frozen case
The school case
The office case

Each of the clues had to be picked up at different markers positioned around the interaction area (see Figure 4). The location of the

Figure 3: Example of the interactions described in the paper. A group of four participants discuss a murder mystery. One of them is remotely present through a robot, and has to go through several approach/-converse/retreat cycles. The inset shows the interface as seen by the remote participant.

marker for the next clue was provided to the Visitor 75 seconds after the previous clue was presented, which gave ample time for both approach and conversation (we confirmed this in a pilot).

Each group of participants was thus part of a total of eight approach/converse/retreat cycles, separated by the Visitor having to go to a marker to collect the next clue. After these, rather than a ninth clue, the Visitor was given the instruction to go and decide as a group on a primary suspect. This resulted in one last approach, and a discussion that was ended by the experimenter when consensus was reached.

3.2.1.2 *Procedure*

The study took place in a controlled laboratory setting. For the study, we used a Giraff telepresence robot equipped with the hardware required for the data collection. The robot was located in a room with the Interaction Targets (**interaction area**). The Visitor controlled the robot from a separate room using the standard Giraff software (Figure 3).

After a briefing, participants were randomly assigned to either be the Visitor (1 participant) or be an Interaction Target (3 participants). This was followed by task-specific instructions from the experimenter. The Interaction Targets were equipped with everything required for the data collection while the Visitor was given a brief training on controlling the Giraff (changing position, orientation and head tilt).

The Visitor approached the Interaction Targets for a total of 9 times. The first eight times the Visitor approached the Interaction Targets once from each of the eight markers shown in Figure 4. The final approach was from the same marker as the first approach. To eliminate possible ordering effects, the Visitor had to go to the different markers in one of eight randomly assigned counterbalanced orders[4].

At the end of each cycle, before being given the next clue, we asked participants (individually) to fill in a brief questionnaire on the robot behaviour during that cycle. The next clue was presented after all participants had finished filling in the questionnaire.

While filling in the questionnaire at the end of each cycle, the Interaction Targets were asked to stand in a fixed formation which was temporarily projected on the floor. The projections were not shown during the cycles and we explicitly told our participants that they were allowed to move around during the cycles. We used two formations; a circular formation, with every participant occupying an equal amount of space, and a semi-circular formation featuring an open space [76]. Groups were randomly assigned to one of the formations. This was not a condition, as it would have been in deductive research, but instead intended to cover some of the variations that might naturally occur.

At the end of the interaction part of the study, after the group had reached a consensus on their primary suspect, we asked all participants individually to fill in a post-experiment questionnaire.

3.2.1.3 *Data collection*

During the study, a variety of data was collected. Here we will describe the methods we used for collecting objective data with various sensors and subjective data with questionnaires.

OBJECTIVE MEASURES All three Interaction Targets were equipped with uniquely identifiable markers (one on the back of the chest, one on a cap), which were tracked by an OptiTrack[5] motion capture system using 8 infrared cameras. The robot was similarly equipped. The system used allows sub-centimeter level precision tracking of both position and orientation of each marker. We optimized tracking for the centre of the interaction area, to make sure we could properly capture the interaction. Markers near the edges of the interaction area could often not be tracked reliably. To ensure proper tracking of the actual interaction, we informed the Interaction Targets about this and asked them to not get too close to the edges of the interaction area. In the analysis here presented, we will take the marker on the cap worn by the Interaction Targets to represent their position.

4 We used a balanced latin square design for this, controlling for regularities in the order in which positions close-by and further to the previous position would be chosen.

5 www.naturalpoint.com/optitrack/

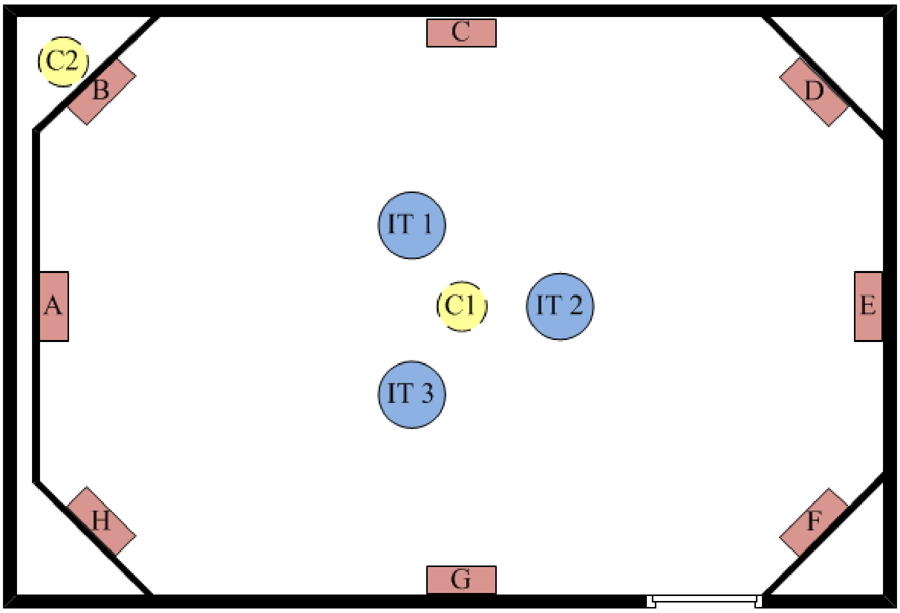


Figure 4: Overview of the interaction area (approximately 6 by 4 meters). On the circle in the middle the positions of the Interaction Targets are indicated (IT1, IT2, IT3), these were projected using a projector mounted to the ceiling, but only in between the approach/converse/retreat cycles. The rectangles near the border of the interaction area indicate the positions of the markers A-H. C1 and C2 indicate the positions of the cameras.

Speech of the Interaction Targets was recorded by equipping them with microphones for close talk recordings. The robot was equipped with a microphone array to record audio and an RGB-D camera (the Kinect).

Two cameras recorded the interaction area. One camera provided a side view, the other a (fish eye) top down view. All interactions of the Visitor with the interface were recorded with screen capture software.

After each approach/converse/ retreat cycle (i.e. 9 times), all participants were given an in-between questionnaire. After the interaction part of the study a post-experiment questionnaire was administered.

The in-between questionnaire consisted of five questions; two related to the usefulness of the clue and task progress. The remaining questions measured comfortability with the robot operators' driving behaviour during approach and retreat, and the distance to the robot during conversation. For the robot operator, we instead used three questions assessing work load (based on [32]).

The post-experiment questionnaire consisted of 49 items. Among others we measured co-presence and attentional engagement [9]. Furthermore we measured the participants' attitude towards robots [34] and workload [32].

3.2.1.4 *Participants*

A total of 56 participants participated, divided into 14 groups of 4 persons. Of these, 13 (23.2%) identified as female, 43 (76.8%) as male. All were students, aged between 18 and 32 years with a mean of 20 (SD=2.2). Most participants had the Dutch nationality (85.7%).

3.2.1.5 *Data synchronization and segmentation*

After the experiment, we synchronized the data from the various sources in Elan[6] using points that were visually/auditory/motion-wise salient. We used the tracking data to determine when the robot was moving or not[7] and then used that information to segment the collected data. **Approaches** were here defined as the set of movements (and enclosed non-movements) between the Visitor being given a clue and the Visitor starting to (verbally) share that clue with the Interaction Targets. Likewise, **Retreats** were here defined as the set of movements (and enclosed non-movements) between the buzzer indicating that the next clue could be collected and the end of the recorded movement to the marker. The segment in between Approach and Retreat was defined as **Converse**.

In the segment between each Retreat and the next Approach the participants were filling in the questionnaires, we did not use this segment in our analysis. After the ninth Approach, the task of the participants changed, so we excluded that data from our analysis as well.

3.2.2 *Findings*

We will present first findings from the (quantified) observations and the investigation of the relations between features of the dynamics of the motion patterns and the ratings of the Interaction Targets.

3.2.2.1 *Observed patterns of behaviour*

Under the assumption that the participants all tried to display suitable social positioning, suitable behaviours would likely be more common. Thus, patterns that are commonly observed in the interactions can be generalized to hypotheses for suitable behaviour with inductive reasoning. We will here introduce some of such patterns, organized by the phase of the interaction (Approach/Converse/Retreat)

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6 Annotation tool developed by the Max Planck Institute for Psycholinguistics (The Language Archive, Nijmegen, The Netherlands), available from tla.mpi.nl/tools/tla-tools/elan/

7 We defined the robot to be moving if the position of the marker placed on its base, smoothed over 50 frames, changed more than 0.02cm between frames (2.4cm/s). This yielded some false positives.

in which they occurred. Where applicable, we will quantify these patterns and use the tracking data to calculate how common they were.

APPROACH During the Approach, most Visitors drove the robot towards the Interaction Targets (Table 5-1,4). Only in one of the groups we observed that the Visitor only turned the robot to face the Interaction Targets without driving to them.

When approaching, Visitors commonly aimed for the closest-by opening between the Interaction Targets they could see, rather than taking a larger detour to approach the group from another angle (Table 5-3). We only observed one Visitor taking multiple such detours; for this Visitor, the Interaction Targets were in the semi-circular formation and the detours seemed aimed at the large opening in that formation.

In some cases we saw that the Interaction Targets actively changed their position to accommodate the approaching Visitor – e.g. by making the opening the Visitor was aiming at larger and/or by moving a little towards the Visitor. However, this pattern was only moderately common (Table 5-5).

CONVERSE During conversation, many Interaction Targets changed their position between the beginning and the end of the Converse segment, while movement of the Visitor was very rare (Table 5-6,7). When the Visitor did move, these movements were rotations that increased the visibility of the Interaction Targets.

RETREAT In 38 out of the 112 Retreats (33.9%) we observed, to our surprise, that Visitors passed straight through the group. This was always done to reach a marker located directly behind the group. In 42% of these situations the Visitors communicated this beforehand. Only in rare cases (9 cases, 8% of total Retreats) we observed that the Visitor backed up from the group and took a detour instead. The Interaction Targets actively assisted the Visitor, by pointing out the position of markers, by moving out of the way and even by actively inviting the Visitor to pass through the group.

3.2.2.2 *Relating motion patterns with ratings*

The ratings provided by the Interaction Targets during the in-between questionnaire give additional information on whether the displayed behaviour was actually perceived as more or less comfortable. We can thus look for patterns in the relation between this information and (dynamical) aspects of the recorded behaviour. From the relations further hypotheses for suitable behaviours can be derived.

There were large individual differences in how the different Interaction Targets answered the in-between questionnaires, which makes it harder to reliably extract this information. To compensate for

	Quantified pattern	min	Q25	Q50	Q75	max
1	Distance between robot and centre of the group at end of Approach	7cm	91cm	113cm	134cm	315cm
2	Angle (in degrees) between robot viewing direction and centre of the group at the end of the Approach	0°	5°	10°	18°	133°
3	Angle (in degrees) between the actual position of the robot at the end of the Approach and the position it would have had if it had moved in a straight line from the marker to the centre of the group.	0°	9°	18°	34°	135°
4	Distance between first and last detected position of robot during Approach	0cm	111cm	176cm	211cm	293cm
5	Distance between first and last detected position of Interaction Targets during Approach (averaged)	1cm	9cm	13cm	21cm	84cm
6	Distance between first and last detected position of robot during Converse	0cm	0cm	0cm	1cm	233cm
7	Distance between first and last detected position of Interaction Targets during Converse (averaged)	5cm	13cm	20cm	37cm	122cm

Table 5: Quantified patterns of behaviour with a five-number summary (minimum (MIN), lower quartile (Q25), median (Q50), upper quartile (Q75), and maximum (MAX)) of their distribution in the collected data

this, we used Gaussian normalization (normalizing the scores of an Interaction Target by subtracting the mean of those scores and dividing by their standard deviation), ensuring that the scores for each of the Interaction Targets had the same mean (0) and standard deviation (1). These scores were then combined into a score for each group, by averaging over the three Interaction Targets in that group.

We will first describe some informal findings acquired by looking for patterns in the Approaches/Converses/Retreats that had the ten highest and ten lowest average normalized ratings. Then we will discuss more quantified ways for looking at these findings.

MOTION PATTERNS WITH THE HIGHEST/LOWEST RATINGS Driving the robot with a smooth and steady path seems to be important for the average normalized ratings, since we observed this in most of the ten Approaches and Retreats that scored highest, while observing more 'wobbly' robot motion in many that scored lowest.

In most of the highest rated Approaches we additionally observed that the Visitor stopped at on average 1.25 meter from and aimed at the centre of the group, and changed the head tilt of the robot to face the group even better (see Figure 5a). In some of the lowest rated Approaches the Visitor did not approach at all, or got so close to the Interaction Targets that they stepped away (see Figure 5b).

In nine out of the ten highest rated Retreats we saw that the Visitors explicitly communicated their goals (verbally) before driving. The pattern we observed before, in which the Visitor passed straight through the group while retreating, was observed in both the highest and the lowest rated ten Retreats and thus seems to have had no strong influence of itself on the given ratings.

We did not observe any particularly salient patterns in the ten highest rated Converses, but in the ten lowest rated the robot was usually far away from the group centre or relatively close to at least one of the Interaction Targets.

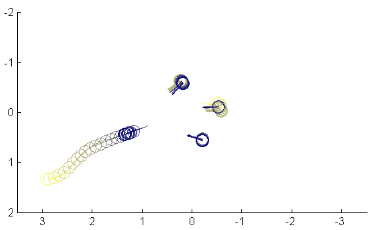
QUANTIFIED RELATIONS WITH RATINGS To further quantify the relations between the ratings and several aspects of the used motions, we looked into how they correlated with each other. As the average normalized ratings were not normally distributed (p=.0306, Kolmogorov-Smirnov) we used Spearman's rank correlation, which is robust against outliers and non-normally distributed data. We did not find a significant correlation with the average normalized ratings for distance between the robot and the centre of the group at the end of the Approach ($\rho = 0.109$, $p = 0.220$), nor for the speed used during the Approach ($\rho = -0.008$, $p = 0.929$). We did, however, find a significant correlation for angle between the direction of the robot and the centre of the group at the end of the Approach ($\rho = -0.218$, $p = 0.014$). This indicates a positive relation between how well the robot faces the centre of the group and the ratings.

There are various ways in which the quantified relations with ratings could further be explored to reveal even more measurable relations. We will go into this in more detail in Chapter 5, where we collected a similar dataset in a more constrained setting to this end.

3.2.3 *Conclusions and discussion*

In this section, we have introduced a study in which a Visitor controlling a telepresence robot went through several approach/converse/-retreat cycles with a group of three Interaction Targets. During these cycles, they together attempted to solve a murder mystery, with the Visitor leaving repeatedly to collect clues. We then identified various qualitative and quantitative patterns in the data we recorded in these interactions; common behaviours, regularities in the behaviours that were rated as most/least comfortable, and a correlation between these ratings and a particular positioning.

All these patterns can be used as hypotheses for more general settings. These could be settings with a different task, different people, and a different robot. As discussed at the beginning of this chapter, it is impossible to know beforehand if such a generalization is justified. For example, since our patterns were found in a setting with a telepresence robot, there is no guarantee they will translate to other types of robots. It is for this reason that our findings at this stage are hypotheses only.

(a) 

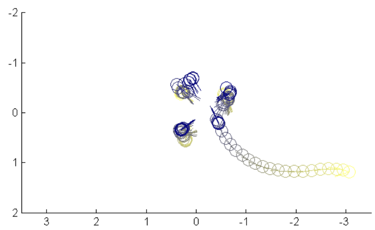
(b) 

Figure 5: Representation of head tracking data from two Approaches, one with a high average normalized rating (a) and one with a low average normalized rating (b). The circles with lines show the positions and orientations of the Visitor and Interaction targets in the interaction area. Indicators near the end of the Approach are darker. Axes indicate distance (in meter) from the centre of the interaction area in the horizontal and vertical direction.

To demonstrate the use of our method, we have used this inductive reasoning to generate a variety of hypotheses on social positioning. These include, in line with what proxemics would pose [31], the hypothesis that a (telepresence) robot should make an approach motion to get within approximately 1.25 meter of the individual interaction targets it wants to interact with. Based on our findings we can also hypothesize a relation between how well a robot faces the centre of a group and how comfortable the group rates that positioning. In addition we found that dynamics indeed play a role in these interactions, since both the Visitor and the Interaction Target adapted their position and orientation to each other in various ways. This for example led to the hypothesis that a robot could pass through a group when retreating without this effecting how comfortable that retreat is.

Given the rich data that we collected, there are many opportunities for further analysis, in particular into the relation between aspects of the motion of the robot and how comfortable it is rated to be.

Overall, we have introduced a quantitative inductive study to robotics research and used it to generate various hypotheses that can guide the design of social positioning robot behaviour. Our findings furthermore show that temporal and social dynamics can play a role in the interaction between a (telepresence) robot and a group.

3.3 LONG-TERM USE OF TERESA IN AN ELDER-CARE FACILITY

The work described in this section has previously and more extensively been reported as a deliverable for TERESA; *[100].*

After the work in the previous section, one important question remained unanswered; what is the effect of an MRP *semi-autonomously* displaying social positioning behaviours in interactions with elderly? Or, to make this more specific, how would the use of an MRP with semi-autonomous social positioning behaviours to mediate in social interactions influence those social interactions?

To investigate these questions, and to gain insight into how such a system would be accepted, we conducted a long-term study in an elder-care facility. We aimed to investigate how social positioning behaviours based on what we found in the previous sections would influence that acceptance. Additionally, we wanted to get insights on ways in which such a system can best be used within the context of a nursing home for the elderly.

A Dutch elder-care group, 'Zorggroup Sint Maarten', had been found willing to host our study at one of their nursing homes in Lochem, the Netherlands: 'Gudula'. Residents of the nursing home would be asked to participate, and the robot would stay at the nursing home for several weeks, participating in a variety of activities.

Our initial plan was to use a mixed method approach, manipulating the use of dynamic socially normative social positioning by the robot, but both the manipulation and the quantitative measures quickly turned out to be unsuitable for the user group. While the qualitative approach and its measures still yielded valuable results, we feel that knowing which parts of our method we had to discard and why will be of added value to others setting up longitudinal studies with robots and/or in nursing homes for the elderly. Therefore, we will first give an overview of our initial planned method (Section 3.3.1) and then briefly discuss all the reasons we had to deviate from this plan (Section 3.3.2). We conclude by describing the method we eventually used, which can be read independently from the other subsections (Section 3.3.3).

3.3.1 *Initial method*

Our initial plan was quite straightforward: We aimed to follow a mixed method approach to investigate the acceptance of a telepresence robot, as well as the influence of the use of semi-autonomous social positioning (or not) on the user experience of our elderly participants. To do so, we would look in the nursing home for a variety of existing recurring activities that were suited for using the telepresence robot. In approximately 6–8 such activities, groups of 4–6 participating residents would be asked to participate in our study for a total of five weeks. Using existing activities would ensure that participants had a prior relationship, to avoid the effects that establishing a new relationship could have on our findings.

The activities would stay unchanged, with the exception of the use of the robot. One of the residents would use the robot from his or her room from the start to the end of these sessions, to truly immerse the participants in the experience. This would be the same resident in each session. Between groups we would manipulate the amount of social positioning used. We would film the interactions, keep an observation diary and perform an evaluation at the end to allow for a qualitative analysis, while questionnaires would give more quantitative insight into the user experience.

Moreover, when we discussed the possibility of doing experiments at the nursing home, we had a meeting in which various staff members were present and actively suggested a wide range of different use cases. To accommodate these, we also arranged for a parallel study in which staff members could test these use cases and report their observations. If necessary, one of us would also be available to provide technical support.

3.3.2 *Reasons to deviate from the plan*

As we quickly found out, our initial plan was unsuitable for this particular setting and these particular participants. We will here give an overview of the findings and the challenges encountered that required us to adapt the initially planned method.

When setting everything up, connecting the robot to the wireless network of the nursing home proved difficult. Even though over the following weeks we made various attempts with help from both the network's help-desk and the robot's help-desk, in the end we could not connect the robot to the wireless network and thus had to resort to setting up a local network using a router. However, this limited the communication range and meant that the robot had to be controlled from a nearby room. This made it difficult to test most of the envisioned use cases. In addition, we found that the network was not reliable, forcing us to cancel two of the sessions halfway through.

The second effect that we had not expected, was the way in which the residents would respond to being potential participants. In this context, it may be noteworthy that we conducted our study in a Dutch nursing home and that due to regulations changing in the past few years, residents of a nursing home almost all have mental and/or physical disabilities. This caused three problems. (1) Most participants were incapable of filling in a questionnaire. Some found it too tiresome, some could not read properly or write properly, some had difficulty with conceptually understanding the questions, some even 'cheated' by copying the answers of others. We therefore replaced the interview with a group evaluation at the end of each session.

(2) Participants seemed scared at the thought of participating in a formal experiment. With help of the staff we had selected participants who were still capable of making independent decisions. They all agreed to participate and to being filmed in the process. Nonetheless, when asking them to sign an informed consent form, we found that this caused considerable stress; they started doubting if they should sign and if they would be "good enough" for the experiment. In one group, we had to first do two sessions without the context of doing an experiment (i.e. without filming) before they retro-actively signed, giving informed consent. (3) We felt that actively displaying less socially normative social positioning might very well negatively influence how the Interaction Targets would view the Visitor. Given the frailty of the involved residents, this did not seem ethically justifiable for a longitudinal experiment with this user group; we felt morally obliged to drop that condition[8].

3.3.3 *Revised method*

In the end, we used a qualitative approach to investigate the user acceptance and experience of a telepresence robot with autonomous social positioning. To do so, we deployed the robot during four sessions of a weekly activity for each group of participants. In every group, one participant was the Visitor for the duration of the study. At the beginning of each session, we set up the robot at a charging station close to the table at which the activity would happen. Then, just before the start of the activity, the Visitor went to an office close to the location of the activity, from which the robot was controlled. The robot was then controlled by an experimenter (Wizard of Oz, or **WoZ**) to join the group and, through the robot, the Visitor participated in the activity. At the end of the activity, the Visitor was asked to say goodbye to the group, after which the robot was piloted back to its charging station. To wrap up each session, we performed a brief evaluation of that session with all group members. After four sessions, we wrapped up with a fifth, longer, evaluation session in which we did a semi-structured interview and thanked the participants for their participation.

In addition, we had several meetings with involved staff members in which they reflected on the possibilities and performance of the robot, including a final evaluation where we asked more structured questions similar to the ones used with the residents. All these meetings included the care manager, who was responsible for the quality of life of all the residents of the nursing home, a project manager,

8 Note that such ethical concerns may as well play a role for the deployment of a hypothetical 'finished' telepresence robot with semi-autonomous behaviour; any kind of limitation in the semi-autonomous behaviours of such a robot can potentially negatively influence how the Interaction Targets would view the Visitor (see Box 4).

Blame my telepresence robot

In the TERESA project we have looked into semi-autonomous behaviours for MRPs – but how does it reflect on the Visitor if the robot showing their face makes a faux pas? Or, more specifically, if an MRP gets uncomfortably close to you, do you think less of a person shown on that MRP? And, in addition, how is this influenced by whether you think that that person is manually controlling the MRP, or that the robot is driving autonomously?
These questions were investigated by one of our Master students, Josca van Houwelingen-Snippe, in a 2x2 within-subject study, manipulating both attribution (manual control/autonomous) and approach distance (uncomfortably close/not). Her participants (n=20) were approached four times by the robot, which showed a different person each time (counterbalanced), and had to judge those people on their suitability as a room-mate.
She found an interaction effect, where if a robot came too close, participants liked the person less if they thought the robot was driven manually and not semi-autonomous. She also found that failures of a robot best predict an effect of the interaction if we take a memory effect into account.
So how bad is it for a person shown on a semi-autonomous MRP if that MRP makes a faux pas? It depends on whether people know that the robot is driving semi-autonomously.

Box 4: Joint Effect of Proxemics and Attribution on Interpersonal Attraction. This work has been conducted by Josca van Houwelingen-Snippe as part of her master's thesis, whom I had the pleasure of supervising in the process. It has previously been published at Ro-Man 2017 [40].

responsible for overseeing technical innovations, and a staff member responsible for overseeing and organizing activities for the residents.

In the remainder of this subsection, we will discuss the participants, materials, robot behaviours, and collected data in detail.

3.3.3.1 *Participants*

There were not many activities at the nursing home that were both recurring and suitable for deployment of the robot. This is partly because the program at the nursing home changes every week, but also because most recurring activities required some sort of physical interaction for which the robot was not equipped, e.g. card/board games, ring tossing. In the end, we used a group that met over coffee and a group that participated in a quiz activity that was organized for several consecutive weeks especially for our experiment (see Table 1). The quiz activity was organized and supervised by a staff member.

3.3.3.2 *Materials*

For the study we used a standard Giraff telepresence robot (v4.0T). Because there was no need, we did not mount the additional TERESA equipment on it, which had the added benefit of reducing weight and thus increasing manoeuvrability and battery life. We used a Wizard-of-Oz set-up to control the robot. Due to practical restrictions in the environment and the aforementioned connection problems, the controller (WoZ) was located in the same room as the Visitor. The Visitor used a laptop with a built-in webcam, microphone and speaker to

Group	1			1+2		2				
(activity)	(Morning coffee)					(Quiz club)				
Participant	A	B	C	D	E	F	G	H	I	J
Gender	f	f	f	f	m	m	f	m	m	m
Age	$\oslash$	94	82	88	92	90	83	69	87	84
Perception										
Uses hearing aid?	$\oslash$	$\ominus$	$\ominus$	$\oplus$	$\oplus$	$\ominus$	$\ominus$	$\ominus$	$\ominus$	$\oplus$
Hearing problems?	$\oslash$	$\oplus$	$\odot$	$\ominus$	$\ominus$	$\ominus$	$\ominus$	$\ominus$	$\oplus$	$\oplus$
Uses vision aid?	$\oslash$	$\oplus$	$\oplus$	$\oplus$	$\oplus$	$\ominus$	$\ominus$	$\ominus$	$\oplus$	$\oplus$
Vision problems?	$\oslash$	$\ominus$	$\odot$	$\oplus$	$\ominus$	$\ominus$	$\odot$	$\oplus$	$\ominus$	$\oplus$
Experience with...										
Telephones	$\oslash$	$\oplus$	$\oplus$	$\oplus$	$\oplus$	$\oplus$	$\oplus$	$\oplus$	$\oplus$	$\oplus$
Computers	$\oslash$	$\ominus$	$\odot$	$\oplus$	$\ominus$	$\ominus$	$\odot$	$\oplus$	$\ominus$	$\ominus$
Internet	$\oslash$	$\ominus$	$\ominus$	$\oplus$	$\ominus$	$\ominus$	$\odot$	$\oplus$	$\ominus$	$\ominus$
Video conferencing	$\oslash$	$\ominus$	$\ominus$	$\odot$	$\odot$	$\ominus$	$\ominus$	$\ominus$	$\ominus$	$\ominus$
Robots	$\oslash$	$\ominus$	$\ominus$	$\ominus$	$\ominus$	$\ominus$	$\ominus$	$\ominus$	$\ominus$	$\ominus$

Table 6: Demographics of the participants. Ms D and Mr E, a married couple, were part of both groups. Ms A dropped out of the study halfway through, we did not get demographic information from her (indicated with $\oslash$). We used $\oplus$ to indicate a positive answer, $\ominus$ to indicate a negative answer, and $\odot$ as an intermediate (e.g. not sure, sometimes, or only experienced once). When participants used a hearing or vision aid, we asked them to indicate if they still had hearing or vision problems when using that aid.

communicate. The WoZ used a separate screen and mouse connected to the same laptop to control the robot, and used the screen as a barrier between himself and the Visitor. We used a modified version of the Giraff interface with which the Visitor could only see the video feed.

3.3.3.3 *Behaviour of the robot*

Following the findings from the contextual analysis and the exploratory data collection described in the previous sections, and the related work on social positioning (Chapter 2, we designed a range of robot behaviours to be used by the WoZ. The WoZ was instructed to conduct all these behaviours concurrently. Given our earlier findings, we defined a static initial approach distance to be used, but then added to that various dynamical behaviours in line with our observations:

1. Approach the group to a distance of approximately 1.25 meter, being as close to the table as the closest group members;
2. Lower the head of the robot when interacting with seated people, and raise it when interacting with standing people or when navigating;
3. Aim the robot towards the centre of the group with which it interacts, or turn to face the person with which the Visitor is talking if the conversation seems to be mainly one-on-one;
4. While in an interaction make small head-tilt and rotation movements to prevent the robot from appearing static [23]; and
5. When hearing problems occur, change the volume as necessary, and reposition the robot to be closer to the conversation partners if changing the volume does not suffice[9].

This combination of behaviours was tested in a pilot study where the robot was used in a pub quiz by convenience sampled participants of varrying age (n=10), confirming that it was indeed perceived as social positioning.

3.3.3.4 *Collected data*

We collected video data: (1) by recording the Giraff interface using ScreenCapture software; (2) with a camera on a tripod viewing the interaction; and (3) with an omnidirectional camera placed at the centre of the table around which the interaction took place. During many sessions we could not collect video data, e.g. because the participants had not given consent, or because there were visiting school children who we did not have permission to film.

9 This adaptation is based on the leaning behaviour observed in our contextual analysis, and has been tested in a study that we report on in Chapter 6.

We asked the opinions of the residents at various points during the study. Before introducing the robot, there was a brief session in which they gave their opinions about care robots for elderly. After each session, we did a brief evaluation of that session with the participants.

Next, after all sessions were over, we organized a longer final evaluation with the participants, in the form of focus groups. To guide the discussion, we used various open questions about the experiences with the robot. We asked questions about; (1) how they felt now about having a session without the robot, after several weeks with it, (2) about the interaction with the Visitor, with questions on realism, presence, and on how the social interaction was perceived to change, (3) perception of the robot and its behaviours, (4) where, when, and for whom, they thought the robot should be used, and (5) how they would feel if the robot would be deployed (mostly) autonomously. We also asked if participants would be willing to chip in for repairs, if necessary[10]. We closed each focus group with questions on the demographics of our participants.

We kept an extensive observation diary, in which the principal investigator made notes shortly after all activities in the nursing home involving the robot and later expanded these into human-readable reports. As an additional independent source of information, the staff member overseeing the activities with group 2 also made short reports of each of these sessions.

Lastly, during the aforementioned meetings with involved staff members at the beginning, middle, and end of the study, we also did evaluations of the system. In the final evaluation we asked more structured questions, similar to the ones used in the final evaluations with the residents.

In this document we will focus our reporting on the observation diaries, as well as on the evaluations of both residents and staff.

3.3.4 *Results*

As discussed above, we collected a wide range of data during the sixteen sessions in which the robot was used, and four evaluation sessions, see Table 7 for an overview. These sessions suffered from a variety of technical challenges. While acknowledging the bias introduced by this, we have also identified a variety of more social challenges. An overview of the various challenges identified, roughly grouped by topics within the themes 'technical' and 'social', can be found in Table 8 and 9 respectively.

10 This question in particular has most likely been very sensitive to social desirability in the answers. As such, this question was explicitly *not* intended to get a particular numerical value, but rather as a starting point for further discussion on the perceived value of the robot.

To give an impression of our more long-term results, we will further give a more chronological overview of the experiences of group 1, group 2, and in general. These overviews are primarily based on the observation diaries and the evaluations, and, together with Table 8 and 9, highlight the findings on which our conclusions in Section 3.3.5 are based.

3.3.4.1 *Experiences of the morning coffee group (group 1)*

The morning coffee group (group 1, Table 6) meets for coffee for most mornings on week-days. They always sit at the same table in the common area of the nursing home, usually with each of them in their 'own' spots. Coffee is provided by the restaurant staff of the nursing home. There are some volunteers that often join the different coffee groups to have conversations, but these do not usually join this particular group. Though there is no strict schedule, they all arrive around ten o'clock, and leave approximately thirty minutes to an hour later. Only Ms A is slightly less of a regular, since she does not always join. While together, they talk about the things that are on their mind or just sit together, drinking their coffee in silence.

We invited them to participate in our study, and they all agreed. The involved staff member suggested that we would ask Ms A to be the Visitor, hoping that that would be an incentive for her to join more regularly, and we followed this suggestion. When introducing the procedure for the sessions, we stressed that it was intended as an evaluation of the system, not of the participants. Furthermore, we emphasized that there was no specific way in which we expected them to respond to, use or handle the robot.

Nonetheless, when the robot with Ms A as the Visitor arrived in the group at the beginning of the first session, all the others looked at the robot expectantly. Even though staff later confirmed that in regular interactions they commonly have periods without conversation, with the robot they indicated several times that they expected Ms A to start a conversation. Ms A clearly felt this pressure, as she started stammering and tried to ask the co-located WoZ several times what she should talk about – to which the WoZ only indicated that they were free in their topic of conversation. In the end there was no conversation, which seemed extremely uncomfortable for Ms A. The experimenter therefore decided to end the session. In the evaluation afterwards, one of the group members indicated that "the robot should have said something". Ms A expressed the feeling that she had failed (the experiment) even though the experimenter tried to comfort her. She decided that she no longer wanted to be the Visitor.

In the following sessions, Mr E took the role of Visitor, but unfortunately these sessions were all plagued by various technical problems. From a bad connection (session 2), to a hardware problem (session 3), to very poor audio with lots of environmental noise (all sessions, in

	Group 1				Group 2			
Session	Date	Participants	Visitor		Date	Participants	Visitor	
1	28/9	ABCDE	A		29/9	DEFGHIJ	H	
2	5/10	ABCDE	E	*	6/10	DEFGHIJ	H	
3	12/10	ABCDE	E	*	13/10	DEFGHIJ	H	*
4	19/10	–BCDE	E		20/10	DEF–HIJ	H	
evaluation	26/10	–BCDE	–		27/10	DEFGHIJ	–	

Table 7: Quick overview of the schedule of the different sessions for both groups of participants. In addition to the sessions listed in the table above, the robot was used at eight activities, ranging from playing bingo to PR events. The robot has first been used at the nursing home for the elderly on Monday 14/9/'15 (introduction of the robot). The last use of the robot was on Tuesday 10/11/'15 (saying goodbye to the robot, and showing it to visiting care-givers). Sessions which (partly) suffered from technical issues that prevented the use of the robot, such as a failing connection, are indicated with a '*'.

particular session 4). In none of these sessions did the communication during the activity come any further than talking about the quality of the audio and the connection. In session 4, at a certain point the group members turned away from Mr E, the Visitor, and started to ignore him – despite his urgent request that they tell him 'if he could be understood'. During the evaluations after each of these sessions, these technical problems were mentioned by the participants several times. In particular the problems with the audio and the influence that had on the conversations received lots of comments; they asked the experimenter what caused these problems, and asked several times if this could be fixed for future sessions.

These technical problems were also mentioned several times during the final evaluation. For example, one participant explicitly said that she "would not trust a robot like this if it were to be used to do an operation in the hospital"[11]. At the same time, they did indicate a feeling that Mr E neither acted nor looked differently through the robot – even though he obviously did not sound as he would in person. They did not seem to have been aware of the behaviour of the robot, only mentioning its navigation skills when asked. The group was quite productive in coming up with potential uses for a hypothetical future version of the robot without technical problems, including using it to attend religious gatherings, and staff using the robot to visit and check for the correct use of medication. When we asked them to say

11 We were surprised by the way in which this phrasing explicitly considered the use of this technology in a completely different situation. We don't know what could have caused this; it can have originated from Ms B recently hearing about such use of the technology, but could also be indicative of her thinking about ways in which robots could be used.

individually if they would donate some money if the robot had been deployed at the nursing home and then fallen down the stairs, all the participants said it would 'depend'.

3.3.4.2 *Experiences of the quiz club (group 2)*

Like the coffee group, all participants in group 2 (Table 6) share a table during the various activities that are organized in the afternoons. They usually sit in the same spot. Since there were no recurring activities that were suitable for deployment of the robot, the involved staff member proposed to organize and supervise a weekly quiz club with the participants in group 2. Quizzes are organized more often, just not as recurring activity, and the participants in group 2 had all participated in such quizzes various times while sitting together at the same table.

When introducing the experiment to the quiz club, the participants were a bit worried; Mr H was to be the Visitor and looking forward to that. But Ms G, who usually collaborates with Mr H during quizzes, was a bit worried that doing so would be hindered by the robot. At the same time, Mr F and Mr J were negative about the potential use a robot could have for them. They all expressed worry about what they should do – after which we repeated that there was no specific way in which we expected them to respond to, use or handle the robot. When we asked them to sign for their consent in participating in the study, these feelings escalated and they all considered not participating. After discussing this with them and the involved staff member, who had organized the quiz club, we agreed that they would just give the robot a try for the first half of the session, without us making recordings.

When the session started, Mr H was his usual jovial self – actually being a bit more jovial than he was in the later sessions. He started conversations with everybody in the quiz club, actively worked with Ms G and made various jokes at which everybody laughed. There were problems with the audio and understandability, which were all resolved within the interaction. The video for the Visitor had a very low frame rate, but this did not seem to affect the interaction as Mr H has limited eyesight anyway. At the halfway mark, the participants had no problem with continuing the interaction through the robot – so that is what we did. At the end of the session, we did a brief evaluation. The main comment was that the robot had been quite prominent and loud; this had broken their normal 'interaction pattern' in which Mr H and Ms G discuss their answers a bit more privately. They indicated that otherwise the mediation by the robot had not really hindered or altered their interaction. Mr J no longer felt that this technology could have a negative effect, while Mr F still seemed reserved or negative about the robot, even though he did not say much.

Over the following sessions we saw that various aspects of the activity were adapted to accommodate for the limitations of the robot, mostly instigated by the involved staff member. They put the teams further apart, creating space between the team with the robot and the other teams, which helped them all to discuss their answers more privately (session 2). Because of the noise in the common area, they then moved the activity to a separate room (session 3). However, that room had a lot of echo, so they then decided to do the quiz individually so that they would not be discussing simultaneously (session 4). Despite us not making any technical changes to the audio, they were most positive about the audio in session 4, both in the evaluation directly afterwards and in the final evaluation session.

Apart from these changes, the quality of the interaction seemed to be mostly dependent on the quality of the audio and the specific circumstance. For example, in the second session there was a lot of noise in the environment and the quiz was printed with each of the illustrated questions on a separate page – this caused considerable synchronization difficulties for Mr H and Ms A, since they were often looking at different pages. They did try to resolve this, e.g. by showing pages of the quiz to each other, but this required so much effort that they later reported that it had prevented their regular collaboration. Likewise, the third session contained questions with blank spaces that had to be filled in, but Mr I, who read them to Mr H, did not indicate the blank spaces; this resulted in weird sentences, which made it harder for Mr H to participate in the quiz and general interaction.

In the final evaluation, there were critical voices about the potential use of the robot for themselves, particularly by Mr F and Ms G. Mr F expressed the opinion that robots could not do things independently. Ms G expressed herself afraid that the robot would be used to replace human contact; she became more positive when she realized that there would always be a human Visitor. She also indicated that she expected she would have a scare if she were to meet the robot in the hallway, later adding that this was perhaps no longer the case after the experiences she had had with it during the study. When we asked them to answer for themselves if they would donate some money if the robot had been deployed at the nursing home and then fallen down the stairs, all but Mr F ('no') and Ms D ('depends') answered with a definitive 'yes'.

They had not noticed much about the social positioning, but when asked the question there were some things they would have liked to see. During the fourth session, the robot had been harder to see for Mr J, as Mr F was sitting in between him and the robot; Mr H then suggested that the group should form a half-moon shape around the robot. We indicated that this would be less 'human-like social', but even then the general consensus was that the robot should perhaps do this[12].

3.3.4.3 *General experiences*

NAME OF THE ROBOT – We introduced the robot to the nursing home as 'TERESA'. Throughout its presence at the nursing home, we saw that residents and staff mostly referred to it as 'her', which is suggestive of acceptance [89]. After some weeks, some staff members decided to give the robot its own name badge – which are usually only given to staff members. In group 2, at a certain moment they discussed the name TERESA as being too feminine when used with a male Visitor and eventually suggested the more Dutch-sounding, but still feminine, alternative 'Johanna'.

EVALUATIONS WITH THE STAFF – We had meetings about the project with the staff in the beginning, middle, and end of the project. In all these sessions, they were actively thinking about how the robot could be used – usually involving the needs of specific residents. For example, they were all quite disappointed when the robot still had connection problems and thus could not be used by a bedridden resident to participate in an activity she would have liked to attend. Likewise, they quite readily came up with a plan of how the robot – even with all its current limitations – could already be used; setting up the activities such that at least one activity each week would be suitable for the robot and then inviting bedridden residents to use it. At a certain moment they even started discussing options for arranging volunteers who could control the robot as the WoZ did during the study. In line with all this, when asked how much they felt repairs of the robot would be worth, they explicitly and pro-actively started thinking about how to pay for repairs given the current budget restraints faced by nursing homes. With that in mind, their answers still ranged from €1000 to €2500.

ACCEPTANCE OF THE ROBOT – We want to mention three interesting cases here. First, when the robot was first introduced, a staff member being the Visitor, there were residents who addressed her as usual by asking her to arrange something for them. Second, there was only one resident who was visibly scared by the robot, when it suddenly and unexpectedly started to move while he passed by. We comforted this resident and saw that a few weeks later in the same situation he was no longer scared. Third, when the robot was driving around the common area, all residents in many ways treated it like

12 We don't really know what motivated this; it could indicate a clear desire for the functionality, stronger than a desire for social behaviour. On the other hand, given that the residents had not really noticed the social positioning, it could also be indicative of them either being unaware of its relevance.

they would treat a human; greeting it, passing it closeby, and waiting to let it pass.

MEDIA AND PR – Placement of the robot in the nursing home quickly attracted the attention of both the local and national media. The attention of the media gradually reduced after the first weeks. Furthermore, at the request of the nursing home, we deployed the robot at several local PR opportunities.

3.3.5 *Conclusions and Discussion*

We have discussed a study where we used a telepresence robot for several weeks in a nursing home for the elderly. Within this study, we aimed to investigate how a system such as that envisioned by the TERESA project could work in long-term real life use, and how it would be accepted. In addition, we aimed to get insights into the ways in which such a system can effectively be used within the context of a nursing home for the elderly. An overview of our findings has been given in the observation summaries (Section 4.1, 4.2, and 4.3), as well as in the identified challenges (Table 8 and 9). Based on these we will here suggest a series of hypotheses and suggestions with respect to experiments, technical challenges, trust, social acceptance, and social participation. We emphasize that given the qualitative methods used, these should be seen as just that, not as supported theories.

EXPERIMENT – We noticed that among the residents cognitive and physical impairments were very common, and, possibly related, they often expressed feeling/fearing "not to be good enough". We think this was cause for several of the challenges we faced in the experiment; e.g., having to sign official consent forms caused stress in our participants, questionnaires were not appropriate for them.

TECHNICAL – As discussed above (e.g. Table 8), we ran into various technical challenges. Most of these had to do with hardware and configuration. However, we feel the problems with the audio went deeper than that and are likely to be caused by the setting as well. Unclear pronunciation, environmental noise, and hearing problems all contributed. Indeed, when these factors were intentionally reduced for group 2 they all reported feeling that the quality of the audio had increased. This suggests that problems with the audio may occur even with state-of-the-art hardware and configuration, and may have to be solved by limiting the settings in which the system is used.

TRUST – Trust seemed to be multi-faceted for our participants. Technical issues made the robot appear less reliable, as indicated by Ms B when she said that "she would not let the robot operate on her in a hospital". At the same time, there seemed to be a lot of implicit trust in the safety of the robot, as almost none of the inhabitants took a wide berth of it during navigation. There were some exceptions but these seemed related to novelty, e.g. the resident who got scared when the robot suddenly started to move nearby, but only the first time.

SOCIAL ACCEPTANCE – There were many indicators of a strong social acceptance of the robot. Residents and staff were very open to the technology and thought along about how the robot could be used (for them). They actively adapted to the limitations of the robot. This may be specific to this nursing home, but they pro-actively came up with various ideas for adaptations. Further, they referred to the robot as a 'her', and tried to personalize it by giving it a name badge and asking if they could rename it. Lastly, all involved staff members thought repairs of the robot would be worth €1000-€2.500 – actively discussing how they could make such funds available within budget restraints – and similarly, most participants in group 2 would be willing to chip in to pay for repairs. In contrast, all participants in group 1 said it "would depend", which may have been caused by the robot performing less reliable in the sessions they experienced.

SOCIAL PARTICIPATION – In most cases, it seemed that all residents treated the Visitors much like they would have been treated in person; with jokes, team-work, requests for help, etcetera. Only when technical problems hindered most communication, we sometimes saw that the Visitor was being ignored. The used robot motion did not seem to have any negative effect on this; during the evaluation participants all indicated that they had hardly noticed it, which suggests that the used behaviours were appropriate, non-intrusive, and non-obtrusive. Only in response to sudden bigger displacements did we see some surprise, particularly in the Visitor.

At the same time, we also saw some potentially negative effects on the interaction. First, the communication through videoconferencing seemed to have a minor constraining effect; we saw (a need for) more synchronization, especially when artefacts such as a printed quiz were involved. Second, we saw an effect of novelty pressure; being telepresent seemed to put pressure on the Visitor to perform as an interesting conversation partner. This made one participant more jovial, but made another so nervous she no longer dared to say anything.

In hindsight it may sound obvious, but although we experienced in this study that a real-life setting does not allow for a controlled quantitative study, we found that instead it makes for a valuable reality check. Our reality check involved: (1) the assumptions in the

Type	Findings
Connection	• The quality of the connection fluctuated heavily in all sessions. This commonly led to frozen video (which could be resolved by the WoZ), and we completely lost connection several times. We could identify some of the causes; (a) distance between robot and router, (b) use of a wireless microphone, and (c) the electric sliding doors of the nursing home causing interference.
Environment	• Navigation was rarely hindered by the environment. Probably because a nursing home is already optimized for easy navigation and accessibility for its residents.
Audio	• Communication was influenced by the quality of the audio in all interactions. In most cases, the Visitor frequently expressed difficulty in understanding the Interaction Targets and vice versa. In some cases the conversations through the robot did not go much beyond this. At the same time, the experimenter could in many cases follow the interaction while the residents indicated they could not. Probable causes are (a) metallic quality of the audio, lacking most lower frequencies, in combination with (b) hearing problems of the residents, (c) noisy environments and (d) unclear pronunciation of residents. Residents were most positive about the audio during activities with little environment noise.
Video	• There were no complaints or negative remarks about the quality of the video; participants were quite positive, despite the fact that in some cases connection problems had caused the video to freeze.
Social positioning	• In a few cases, the WoZ moved the robot to another location with the aim of increasing understandability by being closer to conversation partners. These movements were always followed by expressions of surprise, in particular by the Visitor.
	• We saw none of the residents making detours around a navigating robot; they did not seem to be afraid to get close to the robot.
	• None of the Interaction Targets made remarks about the social positioning of the robot. Only when explicitly asked, some gave suggestions – many indicated even then not to have noticed any small movements.
Stability & fragility	• The robot broke down on one occasion by starting to give blocking error notices, and several times because of connectivity problems. Connectivity problems could often be resolved by restarting. During these break downs we had to rely on technical support because there was no documentation.

Table 8: Overview of the various identified challenges and opportunities that originated in the more technical aspects of the robot.

Type	Findings
Novelty	• Various non-elderly visitors broke into activities to see the robot, sometimes the residents expressed their annoyance about this. • We overheard many conversations about the robot by residents, and numerous others came to visit to see the robot, including local and national media and neighbours of the nursing home. • Primarily during the first sessions the Visitor tried to perform as a 'good' conversation partner, and seemed to feel a pressure to do so. In group 1 this was expressed by Ms A asking the WoZ several times what she should say and eventually seeming to be afraid to say anything anymore. In the final evaluation with group 2, Mr H and others indicated that for this reason he had been more jovial than usual in the earlier sessions. The Interaction Targets in group 1 indicated that they also had the expectation that the Visitor would perform as a 'good' conversation partner.
Perceived Presence – Group	• Possibly related to the novelty, the robot can disturb/influence the activity. Its volume can disturb people and prevent private conversations, its presence can make people feel like they should have a conversation. It can ask undue attention from the staff, for example to help out with synchronization. • When communication is limited (e.g. sound problems), some residents stop communicating with the Visitors, often without explaining this to the Visitors, to their frustration. • Without exception, all residents seem to talk through the robot as if talking with a regular person. This goes from making jokes to asking a telepresent staff member to arrange things as usual.
Perceived Presence – Visitor	• During most quiz sessions, there was a lot of 'synchronization'; communication aimed at ensuring that everybody is figuratively (and sometimes literally) on the same page. This was mostly initiated by the Visitor. Probable cause is that all communication for the Visitor necessarily goes through the screen or audio, which makes other kinds of information sharing, such as watching along on a quiz form, difficult. It may also be related to the individual, as the Visitor in this group had bad eye sight. • As also mentioned in Table 8, the different Visitors all communicated quite often about the quality of the communication and their understandability.
Interactions	• The staff clearly started adapting the activities and communication to the use of the robot, even with only four sessions. This seems to be similar to the way in which they adapt to the different needs of the residents. • We saw that the Visitor talked mostly, though not exclusively, to the people closest to the robot.
Acceptance	• Residents asked many questions about the use scenarios and were actively discussing about the added value these could (not) have to them. • Most people refer to the robot as 'she' and 'her', even if it breaks down. • The robot was personalized by giving it a name badge and by discussing alternatives for its name. • When wrapping up the experiment, both staff and residents indicated that they would miss the robot. Ms G asked if she could say goodbye to the robot.

Table 9: Overview of the various identified challenges and opportunities that originated in the more social aspects of using the robot. Some of the challenges listed in Table 8 also had an effect on social aspects, in particular those involving audio and social positioning of the robot. To reduce redundancy, we have not repeated those here.

planned use cases and experiment design, (2) the technical specifications of the project, and an investigation into our initial questions on (3) social implications and acceptance of the technology, including the robot's semi-autonomous positioning behaviours.

Our findings entail a range of recommendations and hypotheses that could have only been identified in a long-term real world setting. For future experiments in nursing homes, we have made various suggestions as to how not to approach the frail and diverse user group of elderly. We identified unexpectedly large problems with the audio of the robot, as well as various hardware, setting, and user factors that could have caused them. Both social acceptance and trust in the system seemed to be workable, more so after initial novelty effects had passed. We saw that the telepresence system could really support social participation, but also identified potentially negative aspects, such as the increased need for synchronization and the novelty pressure.

Most directly applicable within this thesis, is that we found minimal adverse effects of the robot's semi-autonomous positioning behaviours; only when the robot suddenly moved to a completely different spot did we see a reaction in our participants, particularly in the Visitor. All other dynamic behaviours of the robot were not really explicitly noted by our participants, suggesting that they were seen as mostly natural. In addition, the inhabitants of the nursing home all seemed very comfortable while moving around the robot with its dynamic behaviours. This suggests that the dynamics found in the previous sections of this chapter may well also apply to a robot that moves semi-autonomously, and may thus well be used for the better, at least in the context of TERESA.

These findings are neither quantitative nor quantified qualitative, which means that they can at most serve as inspiration for issues to try and avoid, and questions to try and answer. We hope and expect that these inspirations and questions can help inform future research both within and out of the TERESA project, as well as deployment of (semi-autonomous) (telepresence) robots in similar real-life settings.

3.3.6 *Acknowledgements*

We are very grateful towards the people from the care group 'Zorggroep Sint Maarten' for allowing us to conduct the long-term study described in this section at their nursing home for the elderly 'Gudula', located in Lochem, the Netherlands. We thank Richard Jeunink for making the necessary arrangements, Ans Lensink for welcoming us at Gudula, and the residents and staff for trying the robot with us at various occasions. Special thanks to Irma Mulder and Marry van Veenen for guiding the activities at those occasions and to the former for sharing her observations thereof with us. We have really

enjoyed the open and active attitude towards both us and the robot of everybody at Gudula.

3.4 CONCLUSIONS AND DISCUSSION

> Imagine someone with hearing problems leaning towards a robot, trying to better hear and understand the metallic sounds coming from its speakers – what if the robot would try to maintain its interaction distance and move away from that person in response?
>
> Imagine a group parting to let a robot pass – what if the robot would take an even larger detour as it keeps trying to navigate around the group?
>
> Imagine another group *not* parting to let a robot pass – what if the robot would try to navigate right through the centre of that group?
>
> Imagine someone being scared of a robot, taking a step back in fear – what if the robot would follow that person, maintaining what it believes to be a comfortable distance suitable for conversation?

In this chapter, we have discussed a broad exploration of social positioning for a telepresence robot in the context of TERESA. For our contextual analysis, we observed interactions between elderly during a range of activities. For our inductive study, we collected rich data on interactions between small groups and a person manually controlling an MRP. And in the last study discussed in this chapter, we looked at the long-term use of an MRP with various dynamic behaviours. What these studies have in common is that they all gave insight in an aspect of the context of TERESA. As all three studies were inductive in nature, we cannot make claims about the generalizability of these findings, only pose hypotheses about what might underlie the observed patterns. In our discussion here we will focus on the findings on social positioning behaviours, as those are most directly related to this thesis; for the other findings, we refer to the conclusions of each of the individual studies.

Together, the studies discussed in this chapter have yielded an impression that plays a key role in this thesis; social positioning is not something static, but instead a rich interaction dynamic. We feel this is best illustrated by the leaning behaviour we observed in our contextual analysis; if, in a conversation, one of the elderly involved had hearing problems we often saw conversation partners leaning in while speaking to accommodate (and stop leaning while not speaking). But we saw several more examples of this interaction dynamic, also in interactions involving the robot; from meaningful reactions to uncomfortable robot behaviours, to even letting the robot pass right through the centre of the group.

We further saw that when the MRP used various dynamic behaviours semi-autonomously, participants did not seem to be consciously aware of those behaviours As they *were*, in contrast, quite aware of all the areas in which they saw the robot as lacking (e.g. sound quality, connectivity), we suspect that such small dynamic behaviours can be perceived as so natural that it hardly warrants explicit attention. This also aligns with how close people allowed the semi-autonomous robot to get to them during conversations and navigation.

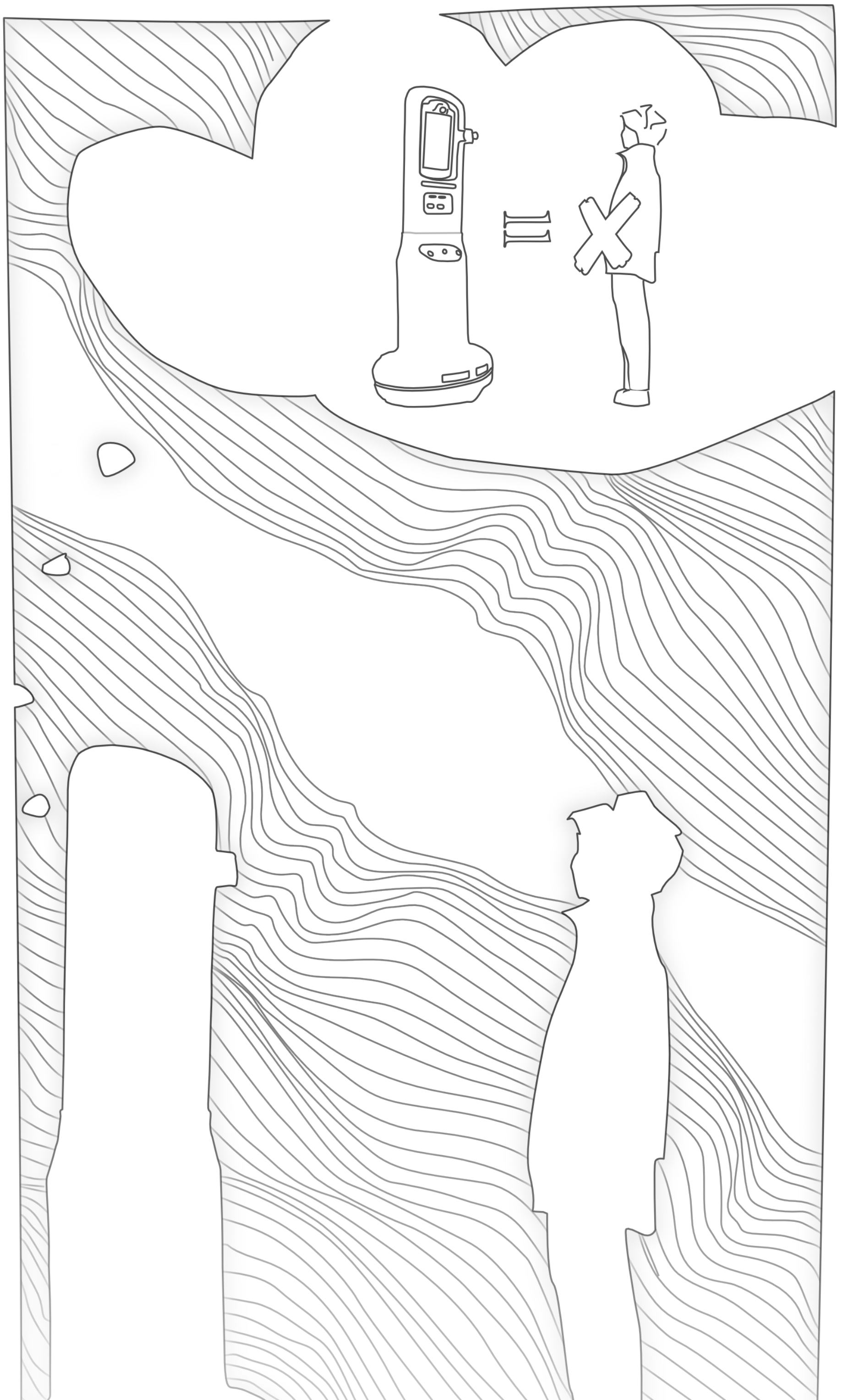
In all, these findings suggest that, in addition to more static factors such as using an interaction distance of about 1.25m, there are various relevant aspects of social positioning that are more dynamic. People respond to (perceived) failures, people adapt continuously, and people signal the need to adapt to each other. And, quite importantly, we saw that people treat the social behaviours of the robot in much the same way, even to the point of seemingly accepting the dynamic positioning behaviours of a semi-autonomous robot in the long-term evaluation. Throughout our observations, social positioning compared best to a dance; a continuous physical adapting to each other, interpreting the actions of others as feedback to improve our own.

This does raise an important question; if social positioning is a rich interaction dynamic, a 'dance', how can social robots effectively be a part of that dynamic? Though the route to arrive at it is quite different, this is similar to the question we found through studying the related work in Chapter 2.

One key aspect seems to be the different social signals people give and that a robot could respond to. For example, that if someone with hearing problems leans towards a robot, the robot could take that as a cue to move closer or turn up its volume. Or, that if a group shows willingness to let a robot pass through their centre, the robot could gracefully accept. Or, that if someone steps away out of fear for a robot, the robot could take that as a cue to give that person more space.

As we will formulate in more detail in the next chapter, these different social feedback cues and the idea that a robot could respond to them, form the seed for the concept of responsiveness.

You don't stop dancing
Because you grow old
You grow old
Because you stop dancing



In this chapter, based on the dynamics observed in Chapters 2 and 3, we give a formal definition of responsiveness as an approach to dynamically generating behaviour. In doing so, we also specify the components and assumptions that an implementation of responsiveness would depend on: detection of social feedback cues (Chapter 5), implementation of improvement strategies (Chapter 6), and testing the assumption that people consider the presence of social feedback cues a 'reason' to use an improvement strategy (Chapter 7). In addition, we explicitly consider the relative advantages and disadvantages of a responsive approach as compared to the setting-specific approach, which is less dynamic and currently commonly used in social positioning for robotics.

Parts of the work described in this chapter has previously been published [101].

4 FORMALIZING RESPONSIVENESS

In the previous two chapters we have described social positioning as a 'dance', a rich and social back-and-forth. We have discussed a range of (non-verbal) social cues that seem to be related to social positioning behaviours and the dynamics that these allowed for. A very clear example is the leaning behaviours we observed, where elderly would lean towards each other during conversations to accommodate hearing problems; people would lean more or less towards each other depending on whether they were talking, about to talk, or about to stop talking.

At the same time, we observed various reasons why there would be practical challenges to capturing social positioning behaviours in general rules (we will refer to approaches using such static general rules as **setting-specific**) – even though this is, as seen in the related work, very much the dominant paradigm. Within the context of TERESA, we clearly saw that there are large and important individual differences that might not be appropriately covered in general rules. For example, we should not treat someone who is afraid of a robot the same as someone who is fascinated by it. We found in the related work that attempts at defining such rules, such as those captured in proxemics, quickly resulted in a very large set of factors that should all be taken into account for proper application of those rules. This raises the question of how an agent can properly take such a large set of factors, and their different combinations, into account. To further complicate matters, many of the factors that we found would be hard to observe in practice – how to properly classify, from just looking at a person, factors like hearing problems, fear and other mental states, bad eyesight?

How can we incorporate these findings into a consistent theory on the dynamics that play a role in social positioning? It is from this question that we first got the idea of responsiveness; the idea of using the 'dance' we saw as an approach to circumvent having to fully capture appropriate behaviour in general rules. Or, to phrase this as a question; is it truly necessary for an agent that wants to find appropriate behaviours to have prior knowledge of general rules on what behaviours will be perceived as appropriate in a particular setting?

At the root of the idea of responsiveness is an interpretation of the social cues that we found in Chapters 2 and 3 as *feedback*, that can be used to inform how an agent can try and improve its behaviour. This feedback can be anything from asking someone not to speak too loud, or cupping a hand to your ear to indicate hearing problems, to taking a step back if someone gets too close (e.g. [18]).

This chapter is dedicated to more precisely, and formally, describing the idea of the responsive approach. We will also provide a formal description of the setting-specific approach. Doing so allows us to give a thorough theoretical assessment of both approaches and to rigorously argue for their relative benefits and challenges. Our goal is explicitly not to argue against or in favour of either approach; on the contrary, the approaches could in fact be used to supplement each other. An informal introduction to the arguments posed in this chapter can be found in Box 5.

To ensure that our findings might be applicable beyond the context of this thesis, we describe both the setting-specific approach and the responsive approach as approaches to generating *any type* of behaviour by any type of agent, though we will still primarily illustrate our reasoning with examples on social positioning.

We will discuss the setting-specific and the responsive approach to generating social behaviour, by formally defining them along with their underlying concepts (Section 4.1), further discussing the challenges faced by setting-specific approaches (Section 4.2), and how responsiveness can (partly) resolve these (Section 4.3). Our formal specification of responsiveness allows for a more explicit consideration of its application, limitations, and opportunities (Section 4.4), and will be the starting point for its implementation in the next chapters.

4.1 TERMINOLOGY

As a starting point for the theoretical assessment of the setting-specific approach and the responsive approach, we will here first define both approaches with a precision that allows for such a comparison. Since both approaches are approaches to generating (appropriate) behaviour, we capture them both in terms of functions that return actions for an agent when provided with its observations. We start from the basic building blocks (4.1.1) with which we define agents and interaction (4.1.2) and discuss what makes behaviour "appropriate" (4.1.3). From this, we then define the two approaches (4.1.4).

To make the relations between the definitions within this terminology more explicit, and to ensure a more rigorous specification, we also introduce symbolic representations for our formalisation, building on our earlier work [98][1]. Beyond this section, the symbolic representations will only be used to similarly state claims explicitly and

1 We will adopt several naming conventions;
- Capitalizing a symbol will indicate it is a set
- Underlining a symbol will indicate it is a function

Why robots can't just pick the most appropriate action (and why humans can't either)

Humans are individuals; we have our own likes and dislikes, fears and desires. To some extent, we are formed the same way: we share cultures, have similar bodies, and have many more things in common. And yet, we are each of us a unique melting pot of all these influences.
This means that the appropriateness of an action in a situation can be widely different from person to person. Of course there are commonalities, patterns to be found, stereotypes to be used effectively; at the same time, we are so diverse that each of those commonalities, patterns, and stereotypes breaks down to some extent in individual cases.
Enter interaction.
Assume you want to pick the most appropriate action for interactions with another person.
A good starting point could be to exploit the commonalities, patterns, and stereotypes mentioned above. While they might not be able to accommodate all individual differences that play a role, they might well be the only reasonable starting point we have. In some cases, if those individual differences are small or don't play a big role, this may be enough. Theoretically, from this starting point we can keep adding more and more specifics on the relevant commonalities, patterns, and stereotypes – trying to capture in general rules what is appropriate for the different individuals we interact with. Theoretically, in doing so we can keep extending this set of 'rules' to specialise better and better into the interactions we can reasonably expect.
Practically, the complexity of the individual is beyond what can ever be fully captured in such commonalities, patterns, and stereotypes. We are each of us formed through all the things that have influenced us. In many cases what is appropriate is dependent on a whole history of influences, so extensive and influential that only the person who experienced it all can know their precise twists of what is appropriate for them at a specific moment, and what is not. Firstly, because the set of potentially relevant influences is so big that an external observer could never take all those influences into account. Secondly, because not all potentially relevant influences are observable for an external observer.
Consequently, it is impossible to know with certainty what is the most appropriate action for interactions with another person – simply because we cannot possibly know with certainty what someone else will perceive as appropriate. Exploiting the commonalities, patterns, and stereotypes can bring us a long way, and work better in some cases than in others, but in the end is inherently limited for interaction with actual individuals.
How can we handle this conclusion – how can we interact if it is impossible to predict fully what would be the appropriate action?
One solution is to enforce your commonalities, patterns, and stereotypes. To establish a set of formal or informal rules for interaction that everyone should follow, i.e. to create a culture. Or to create a lab setting, which can similarly limit peoples' responses. Another solution is to actively avoid interaction with everyone who does not fit your patterns. And of course, one can always just pick the behaviour one thinks to be most suitable, and expect those they are interacting with to just accept it.
But these solutions, while having their merits, are missing out on the beauty of our diversity – on the opportunity to be enriched and to adapt. They put limitations on the people around us by requiring them to act or respond in particular ways.
We propose responsiveness as an alternative solution. For, while it may be impossible to always pick the appropriate action at the first go, interactions consist of a whole dynamic of actions – hence the name '*inter*actions'. Crucial to the idea of responsiveness is that people can give social feedback cues to signal how they perceive the appropriateness of earlier actions. Based on these cues one can then, ideally, effectively hone in on the appropriate behaviour. Because the feedback is given by the person one is interacting with, this effectively boils down to using people themselves as the way to figure out what behaviours they consider to be appropriate.
As such, responsiveness is an efficient way to avoid the aforementioned problems involved in trying to (directly) observe all the factors that influence what is appropriate behaviour to an individual.
One important distinction to make is that responsiveness need not imply learning. Where responsiveness has a focus on reactively adapting within the interaction, learning is more focused on adapting after (inter)actions and presupposes (and depends on) an awareness of the underlying patterns. Various forms of learning can in that way suffer from the dependency on observing all relevant factors that we discussed above. That said, responsiveness and learning can of course complement each other quite effectively.
In conclusion, it is impossible for any robot, or human, to always pick the most appropriate action a priori – but we *can* be responsive to the interaction to jointly find what is appropriate.

Box 5: Formalizing responsiveness; an informal introductory essay specifically. Therefore, this section has been written such that it could also be followed without the symbolic representations.

4.1.1 *Variables, time spans, and value assignments*

We will treat agents as entities, which are roughly separable from the setting in which they exist, and that gather observations and produce actions based on those observations. The state of the setting causes the observations and can in turn be influenced by the actions that the agent produces, allowing for interactions (Fig. 6).

Actions, observations and the state of the setting will all be formalized as *value assignments* to a particular set of *variables* over a particular *time span*.

VARIABLES Our first building block are the **variables** (denoted by v). Each variable v has a **domain** (D_v), which is the set of values that variable v can take. A **variable set** (V) is a set of variables, each of which can have a different domain.

The set containing all variables under consideration is the **setting** (V^S). We will further on in this terminology distinguish several other kinds of variable sets (each with its own symbol), to indicate different ways in which those variable sets will be used.

TIME SPANS Our second building block is **time** (denoted by t). Time too has a domain (D_t), which is a totally ordered set of values, representing a series of successive moments in time. τ_α indicates the first moment of an interaction, τ_ω the last. Moments in between will be indicated with letters such that alphabetical ordering indicates succession, e.g. τ_q comes before τ_r. A **time span** ($\tau_{m \to n}$) between two moments ($\{\tau_m, \tau_n\} \in D_t$, $\tau_m \leqslant \tau_n$) is the complete subset of successive moments in time between them ($\tau_{m \to n} = \{x \mid x \in D_t, x \geqslant \tau_m \wedge x \leqslant \tau_n\}$). Implementations may rely, without loss of generality, on discretised time or event-based observation.

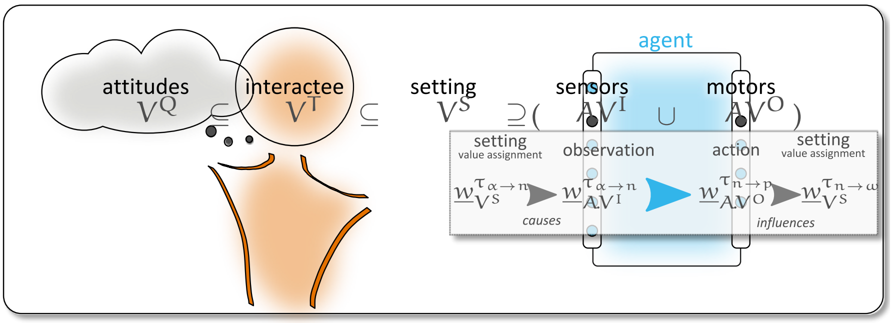


Figure 6: Overview of the terminology involved in the relationship between an agent and the setting in which it exists. Agents map observations to actions.

VALUE ASSIGNMENTS Combining variables and time, we will now introduce our third building block: terminology to describe the value a variable has – or could have – at a particular moment in time. A **single value assignment** for a variable v and a moment in time τ_o (denoted by $\underline{w}_v^{\tau_o}$) is defined as a function that returns the value of that variable at that moment in time ($\underline{w}_v^{\tau_o} : v \mapsto D_v$). We also define a **value assignment** for a set of variables V and a time span $\tau_{m \to n}$ (denoted by $\underline{w}_V^{\tau_{m\to n}}$), as the set of single value assignments for all variables in that variable set and all moments in that time span. The **value assignment set** for a variable set V and a time span $\tau_{m\to n}$ (denoted by $D_{\underline{w}_V^{\tau_{m\to n}}}$) is the set of all possible value assignments for that V and $\tau_{m\to n}$ ($D_{\underline{w}_V^{\tau_{m\to n}}} = \{\underline{w}_V^{\tau_{m\to n}} \mid \cdot\}$).

4.1.2 *Agents and their relation to the setting*

We can now use this basic terminology to represent the different aspects that will play a role in our discussion of agents and their behaviours.

An (artificial) **agent** (denoted by A) has **sensors** (represented as a variable set, denoted by AV^I), **actuators** (similarly represented as a variable set, denoted by AV^O) and "inner workings" to connect those. It produces **actions** (represented as value assignments for its actuators, $\underline{w}_{AV^O}^{\tau_{m\to n}}$) that are affected by its **observations** (represented as value assignments for its sensors, $\underline{w}_{AV^I}^{\tau_{l\to m}}$).

Though in theory the variables pertaining to an agent could be a subset of any setting, we will make some assumptions on the setting to better reflect the real world. We assume that the setting is fully defined, i.e. has a value assignment to each of each variables, from the first to the last moment. We further assume some determinism, such that the value assignment to the setting at one moment is (at least partially) dependent on the value assignment to the setting at the previous moment. Lastly, we assume that the variables pertaining to an agent are also related to other variables in the setting; i.e. that the actions of an agent *to some extent* influence the rest of the setting, and that *to some extent* the observations of an agent reflect the setting.

From these assumptions it explicitly does not follow that an agent will be able to know precisely how its observations are a reflection of the setting (nor how its actions will influence the setting). On the contrary, in real-life settings it seems highly unlikely that from observations we could derive with certainty (part of) the setting behind those observations. There is a wide range of counterexamples, from not noticing that someone has hearing problems (as mentioned in the previous chapter), to missing a step on the stairs, or even hallucinations.

Still, as we *have* assumed a relation between the observations and the setting, an agent could try to estimate (parts of) the setting from its observations. We define the **estimate** function (denoted by $\underline{E}_{AV^I:V}$) such that, for a value assignment to any two sets, here AV^I and a subset $V \subseteq V^S$, it returns an estimation of the value assignment to V ($\underline{E}_{AV^I:V} : D_{\underline{w}_{AV^I}^{\tau\alpha\to n}} \mapsto D_{\underline{w}_V^{\tau\alpha\to n}}{}^E$) . Here the '^{E}' only serves to explicitly signal that this value assignment to a subset of the setting is an **estimation**, i.e. it can be different from the 'actual' value assignment in the setting. The more reliably a value can be estimated by an agent in practice, the more **estimable** it will be said to be[2].

4.1.3 *Appropriate behaviour*

Given our description of agents and their relationship to the setting they are part of, we can now discuss what makes the behaviour of an agent 'appropriate'.

To do so, we first need to introduce the (human) other agents with which the agent is interacting in the setting. We will refer to these as **interactees** (represented as a variable set V^T, subset of the setting $V^T \subseteq V^S$).

Central in describing if the behaviour of an agent in an interaction is socially appropriate, are the **attitudes** of the interactee(s) (represented as a variable set V^Q), loosely defined as a subset of the variables used to express interactees and their properties ($V^Q \subseteq V^T \subseteq V^S$). In the previous chapters we have described a wide variety of attitudes that could play a role, ranging from specific opinions such as "I would not let the robot operate on me in a hospital" to broader constructs such as (dis)comfort, or perception of the agent as competent and/or warm. Attitudes could also be on a specific behaviour, such as the perception of different interaction distances as more or less comfortable that we saw in the related work.

The actions of an agent to some extent influence the setting, which can include the attitudes of the involved interactees. Depending on the goals of the agent, different attitudes can be more or less desirable; for example, an agent may want to avoid scaring interactees, or may want to ensure that participants perceive it as competent, or it may want to do both with a different priority for each. Similarly, an agent that interacts with multiple interactees will need to establish how attitudes of those different interactees can be combined and prioritized.

We thus define **social appropriateness** as a function (denoted by $\underline{P}_{V^Q}$), for a set of attitudes V^Q and a setting during an interaction, that for all possible actions returns a numerical value, such that a higher value indicates that that action would lead to a more 'desirable' value for those attitudes ($\underline{P}_{V^Q} : D_{\underline{w}_{AV^O}^{\tau m\to n}} \mapsto \mathbb{R}$).

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2 A more in-depth discussion of the different ways in which the distance between the estimation and the 'actual' value can be computed is out of scope.

This definition of social appropriateness should not be taken to suggest the agent itself will have access to this function. On the contrary, it is trivial to come up with examples of situations in which people and other agents do not know what would yield the highest social appropriateness – should you kiss that person, what is a proper birthday gift, what is an appropriate interaction distance? As with the settings, an agent could try to estimate the social appropriateness function, but there is no reason to assume an agent would have full access to even part of it.

4.1.4 *Approaches to finding socially appropriate behaviour*

Say an agent has the goal of being perceived as warm and competent by an interactee; then how could that agent achieve that goal if it does not even know precisely what the social appropriateness of its actions would be?

We here define two approaches to finding socially appropriate behaviour, which use very distinct strategies in how they try and get a hold on the social appropriateness of their actions. As introduced above, the setting-specific approach tries to encode an approximation of the social appropriateness function in a set of general rules that help decide which action to pick depending on (particular variables in) the setting. As also introduced above, the responsive approach instead assumes that feedback given by interactees provides information on the social appropriateness of earlier actions that can guide behaviour adaptation resulting in the selection of (more) appropriate actions.

Our definition of these approaches will focus on these strategies, not on the actual implementation of these steps. Different ways of generating behaviour, e.g. static, scripted, learning, dynamic, adaptive, might thus all be used to implement either of the two approaches.

SETTING-SPECIFIC APPROACH The setting-specific approach depends on prior knowledge about how the social appropriateness of different actions is dependent on the values for particular variables in the setting. We therefore define the **knowledge** function (denoted by $\underline{K}$) that, for all value assignments to (a subset of) the setting $D_{\underline{w}_{V^S}^{\tau_\alpha \to n}}$, returns the most appropriate action ($\underline{K} : D_{\underline{w}_{V^S}^{\tau_\alpha \to n}} \mapsto D_{\underline{w}_{V^O}^{\tau_n \to p}}$).

We define **relevant setting variables** (denoted by V^R) as a subset of the variables in the setting ($V^R \subseteq V^S$) such that their values contain all information required to distinguish between setting value assignments where $\underline{K}$ should give different outcomes[3]. A knowledge function that uses at least the relevant setting variables should thus have enough information to select the most appropriate action. Such

3 $\forall_{\underline{w}_{V^S}^{\tau_\alpha \to n}, \underline{w}_{V^S}^{\tau_\alpha \to n}{}' \in D_{\underline{w}_{V^S}^{\tau_\alpha \to n}}} \left[\left(\forall_{v \in V^R} \left[\underline{w}_{V^S}^{\tau_\alpha \to n}(v) = \underline{w}_{V^S}^{\tau_\alpha \to n}{}'(v) \right] \right) \implies \underline{K}(\underline{w}_{V^S}^{\tau_\alpha \to n}) = \underline{K}(\underline{w}_{V^S}^{\tau_\alpha \to n}{}') \right]$

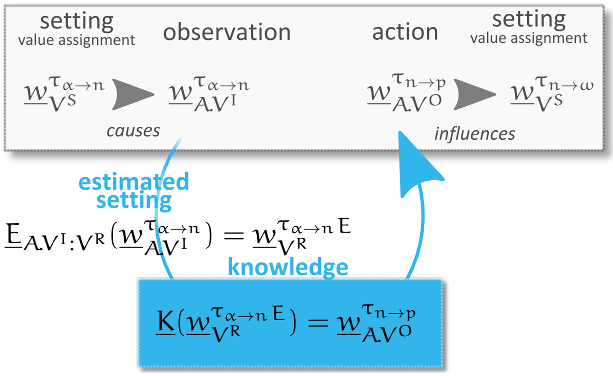


Figure 7: Schematic overview of the setting-specific approach. The agent exists within a specific setting at a specific moment. We will here use, as an example, a setting with a person (male, 1.8m tall, alone, standing, and slightly afraid of the robot). This setting is reflected in an observation of the agent. From this observation, the agent tries to estimate the aspects of the setting it believes to be important; in this example, it might estimate that it is facing a person (female, 1.8m tall, alone, and standing). From these estimations, it then derives what it believes to be the appropriate action using its knowledge; in this example, it might decide to move a bit closer. When this action is send to the actuators of the agent this will in turn influence the setting.

a knowledge function is the ideal, as in practice approximations often have to be used instead (Section 4.2).

From the knowledge, the setting-specific approach works in two steps to produce an action based on observations (Fig. 7). First, the available observations are used to estimate value assignments to (a subset of) the setting. Second, these estimates are used with the knowledge function to try and select the best action. If the knowledge is approximated, or if the relevant setting variables are not fully estimable, there is no guarantee that this will result in an action with high social appropriateness.

RESPONSIVE APPROACH Central to the responsive approach is feedback; any action a of the agent potentially influences the attitudes of the interactee, which can, in turn, be reflected in **feedback variables** (denoted by ν^{φ}). Feedback variables provide **feedback information** (denoted by Φ_a) about the underlying appropriateness of a previous action, which can be expressed as a statement about the relative social appropriateness of that previous action[4]. There are different benchmarks against which can be compared, resulting in different ty-

4 In this specification we have not yet made explicit how an agent can actually establish and/or use this relation between its actions and the social appropriateness encoded in the feedback information. To give an example, if an agents is standing still (the act of doing nothing) and receives feedback information somehow indicating that it should do something else, how would an agent know from that information *what* it should do? We will look into this in more detail in Chapter 6.

pes of feedback information about an action, e.g. if it was optimal[5] or sufficient[6](**basic feedback**), how it compares to other earlier actions[7] (**comparable feedback**), or even which actions would be more/less suitable[8] (**directional feedback**). The **feedback set** (denoted by V^{φ}) is the set of all available feedback variables. A **feedback information set** (denoted by V^{Φ}) is a set of feedback information, expressed as variables.

For an agent to use the feedback, it will have to estimate the relevant feedback information from its available observations. We will for clarity describe this process as first estimating the feedback variables ($\underline{E}_{AV^I:V^{\varphi}}$), and then using those to estimate the feedback information ($\underline{E}_{V^{\varphi}:V^{\Phi}}$). Note that these two steps do not justify any conclusions about the complexity of this estimation, since this can also be expressed with a single estimate function ($\underline{E}_{AV^I:V^{\Phi}}(x) = \underline{E}_{V^{\varphi}:V^{\Phi}}(\underline{E}_{AV^I:V^{\varphi}}(x))$).

Different feedback variables can code (partially) overlapping feedback information and, importantly, the encoding may be flawed. The more estimable the feedback information is from the available set of feedback variables, the more **legible** we will say it to be. Feedback variables can be less legible because they reflect things besides the underlying appropriateness, or because they differ between interactees.

For example, if someone is cupping a hand behind their ear that could be a feedback variable encoding the feedback information that the agent is not using the correct volume settings. To detect cupping would be suggestive that the agent is not using the correct volume settings, but need not be perfectly legible – it might be just intended to scratch that ear, it might reflect on the volume of another interactee instead, or the gesture might be omitted even though the volume settings are incorrect. To improve legibility of the feedback information, other feedback variables encoding the same feedback information could be used as well, such as whether someone is leaning towards the robot while speaking.

The responsive approach works in two steps (Fig. 8). First, the feedback variables are estimated from the available observations, and interpreted as relating to particular previous actions of the agent. Second, this estimated feedback is used to adapt the subsequent actions of the agent. For this, we define an **improvement strategy** (denoted by $\underline{M}$) as a function that, based on all available feedback on previous actions $\underline{w}_{V^{\varphi}}^{\tau_{\alpha \to n}}$ returns a suggested action $\underline{w}_{AV^O}^{\tau_{n \to p}}$, such that, possibly after several iterations, the actions will be sufficient and/or improving ($\underline{M} : D_{\underline{w}_{V^{\varphi}}^{\tau_{\alpha \to n}}} \mapsto D_{\underline{w}_{AV^O}^{\tau_{n \to p}}}$). For example, an improvement stra-

5 Do there exist actions a_2 such that $\underline{P}_{V^Q}(a) < \underline{P}_{V^Q}(a_2)$?
6 Is $\underline{P}_{V^Q}(a)$ larger than a particular cut-off value ('sufficient')?
7 For previous action a_2, $\underline{P}_{V^Q}(a) < \underline{P}_{V^Q}(a_2)$?
8 What is a specific action a_2, such that $\underline{P}_{V^Q}(a) < \underline{P}_{V^Q}(a_2)$?

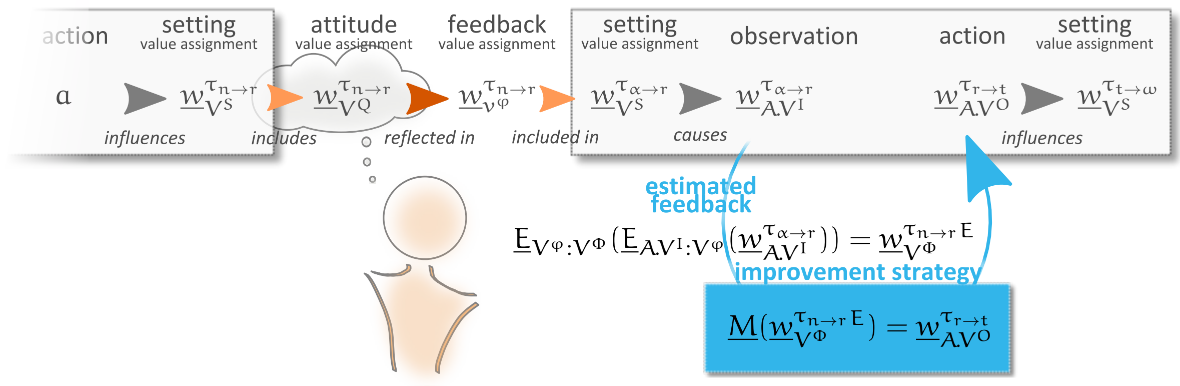


Figure 8: Schematic overview of the responsive approach. Includes an overview of how feedback variables can be assigned a value in response to an earlier action a of the agent. The agent exists within a specific setting at a specific moment. We will here use, as an example, a setting where the agent recently moved away from the person it was interacting with, very much to the dislike of that person. This setting is reflected in an observation of the agent. From this observation, the agent tries to estimate the aspects of the setting it believes to be important; in this example, it might estimate that the person did not really like its moving away. From these estimations, it then derives what it believes to be the appropriate action using its improvement strategy; in this example, it might decide to move a bit closer. When this action is send to the actuators of the agent this will in turn influence the setting.

tegy using comparable feedback could be to try and select actions that are more dissimilar to actions with lower social appropriateness.

4.2 IMPLICATIONS AND CHALLENGES FOR A SETTING-SPECIFIC APPROACH

Assuming that from observations an agent can perfectly derive the relevant setting variables[9], and assuming that the agent has full knowledge of the optimal action for all settings[10], it is trivial to prove that a setting-specific approach will yield the optimal action; for instance, if an agent knows absolutely certain that (a) it is interacting with a 1.8m tall person, and (b) the best action to initiate interactions with 1.8m tall people is always to move to a distance of 1.25m, it is obvious that the agent should move to a distance of 1.25m to initiate interaction. These assumptions will likely hold only in constrained settings, which social interactions usually are not. In this section we will discuss the range of challenges that the setting-specific approach faces because of this.

9 $\underline{E}_{AVI:VR}$ such that $\forall_{\underline{w}_{AVI}^{\tau_{\alpha\to m}} \in D_{\underline{w}_{AVI}^{\tau_{\alpha\to m}}}} \left[\left(\underline{E}_{AVI:VR}(\underline{w}_{AVI}^{\tau_{\alpha\to m}}) = \underline{w}_{VR}^{\tau_{\alpha\to m}\,E} \right) \implies \underline{w}_{VR}^{\tau_{\alpha\to m}\,E} = \underline{w}_{VR}^{\tau_{\alpha\to m}} \right]$

10 $\underline{K}$ such that $\forall_{\underline{w}_{VR}^{\tau_{\alpha\to m}} \in D_{\underline{w}_{VR}^{\tau_{\alpha\to m}}}} \left[\neg\exists_{\underline{w}_{AVO}^{\tau_{m\to n}} \in D_{\underline{w}_{AVO}^{\tau_{m\to n}}}} \left[\underline{P}_{VQ}(\underline{w}_{AVO}^{\tau_{m\to n}}) > \underline{P}_{VQ}(\underline{K}(\underline{w}_{VR}^{\tau_{\alpha\to m}})) \right] \right]$

4.2.1 *Estimating the required setting variables*

For a setting-specific approach to work, it first needs to reliably estimate the relevant setting variables – which poses various challenges. Firstly, as illustrated by the many setting variables we found to be relevant to proxemics in the related work (from dimness of environment lights to extent of being focused on oneself), the set of relevant setting variables will often be very large and, consequently, hard to handle, despite being a subset of all setting variables. In addition, many of the relevant setting variables will only partially be observable, if at all; they may be internal to the interactee (e.g. personality traits, cultural background), include cases that are hard to classify (e.g. gender), or algorithms that reliably detect them may not exist (yet). For example, in the context of this thesis; it would be challenging to evaluate someone's hearing, but as we have seen it could well influence the appropriate interaction distance. See Chapter 2 and 3 for a more extensive set of examples. Though this challenge may partly be resolved by using a reasonable approximation in a limited setting, there is no guarantee that the behaviours based on such approximations would be sufficiently appropriate.

Given the key role that these setting variables play within the approach, these challenges that can **not** be avoided by a purely setting-specific approach. Not taking into account these practical limitations in detecting and estimating the relevant setting variables severely challenges the implementation of autonomous agents that actually use knowledge which depends on these setting variables.

4.2.2 *The knowledge to select the best action*

The knowledge required for a setting-specific approach is in practice usually approximated by a combination of findings from scientific studies. This allows for the design of agents that can effectively select a reasonable action based on a well-chosen selection of relevant setting variables. It also introduces several challenges.

ESTABLISHING WHICH SETTING VARIABLES ARE RELEVANT There is a big challenge to establishing which setting variables are relevant; all aspects of the setting could, potentially, be relevant to generating appropriate behaviour, from smoothness of the floor to the history of pet ownership of the interactee. This poses a challenge because of the sheer number of setting variables to consider, but also because it is hard to predict a priori which variables will be relevant. Though in controlled experiments one can try to focus on specific setting variables, every aspect of the world could, until it has been tested, potentially be a relevant setting variable. Even listing all setting variables would be challenging, let alone investigating their relevance with scientific rigour.

COMBINATORIAL EXPLOSION As the number of setting variables that have to be considered increases, so does the complexity of the knowledge function. If the different variables are dependent on each other, combinations of those factors would also have to be considered to reliably derive the appropriate behaviour. Unless there would be known ways to simplify these dependencies, e.g. by using strong correlations to reduce the complexity, this would result in exponential growth[11].

An implementation of such a knowledge function would thus quickly become intractable. This can partly be avoided by instead using approximations, though this would necessarily introduce uncertainty about the appropriateness of the selected action. The complexity could also be reduced by explicitly establishing which setting variables are independent of each other – but that is a challenging task itself.

In addition, this combinatorial explosion also poses a significant challenge to acquiring the required (prior) knowledge in a scientifically sound way; given the exponentially growing number of combinations, it would be infeasible to test all combinations against each other in a controlled experiment. While approximations may be acceptable for implementations, they are less appropriate for scientific experiments.

STEREOTYPING BY USING GENERALIZED FINDINGS The knowledge function of an agent is commonly acquired through controlled experiments, which investigate how the effects of particular setting variables on particular attitudes could be generalized to a population.

When individual differences play a role in establishing the appropriate behaviour, this can pose a challenge to a setting-specific approach. For example, an agent may well need to adapt its behaviour when interacting with people who had a negative prior experience with similar agents. Or, to take an example from our contextual analysis, there might be a person who just is afraid of a robot at first.

To some extent, these individual differences can be handled by introducing them as setting variables. However, this would pose its own challenges if it introduces (partly) unobservable variables or results in a large increase in the number of variables to be considered.

11 Even when limiting ourselves to 'just' the relevant setting variables (V^R) this would already be $\prod_{v \in V^R} |D_v|$ combinations (since $|D_v| \geqslant 2$ for all meaningful variables, this is at least $2^{|V^R|}$).

4.2.3 *Conclusions*

We have argued that, while the setting-specific approach is in theory capable of being optimal, in practice this would place impossible and intractable constraints both on the estimation of (relevant) setting variables and on specifying and implementing the knowledge function. Thus, it would be impossible to ever reliably achieve such optimal performance with a setting-specific approach. This conclusion still holds when limiting ourselves to just the relevant setting variables, and is applicable to both artificial and non-artificial agents.

Though it is hard to predict how gracefully a setting-specific approach will degrade, it can still be valuable for stereotyping. This is exemplified by, among others, the relative effectiveness of proxemics as an approach to social positioning. Such stereotyping would in particular be viable if a culture provides a small, estimable set of relevant setting variables – or a set that in most cases works as a reasonable approximation. While this is not intended to evoke the (negative) connotations that come with stereotyping, it does share the inherent property that it would not readily individualize.

4.3 IMPLICATIONS AND CHALLENGES FOR A RESPONSIVE APPROACH

The responsive and setting-specific approach are both aimed at finding socially appropriate actions, but are very distinct in how they go at this aim. In this section we will discuss how, as a result, a responsive approach could circumvent some of the challenges faced by a setting-specific approach, and vice versa.

It is trivial to prove that a responsive approach can in theory find optimal actions; assuming perfectly estimable and legible feedback variables, and assuming an improvement strategy that then immediately selects the optimal action based on that feedback, 'the' optimal action can be found immediately after the first action of the agent[12]. Again, as for the setting-specific approach, these assumptions will likely not hold in realistic social interactions.

Since the responsive approach at its core takes a different approach to social appropriateness than the setting-specific approach, they way in which responsiveness will likely be less than optimal is different too. In this section we will revisit the challenges faced by the setting-specific approach, and show how these challenges apply less to a responsive approach. In addition, we will also take a closer look at the challenges faced specifically by a responsive approach.

12 Note that with the responsive approach it is not necessary to assume a static optimal action. On the contrary, responsiveness can result in behaviour that continuously adapts the needs of the interactee – even if they change.

4.3.1 *Estimating the required setting variables*

The setting-specific approach needs to estimate all relevant setting variables, whereas the responsive approach depends only on a estimable and legible set of feedback variables. The more legible the feedback variables are, the more information they provide about the social appropriateness of previous actions (on a set of attitudes), and the less feedback variables a responsive approach will need. If feedback variables are available that are legible and estimable, a responsive approach can thus use these to avoid the aforementioned combinatorial explosion faced by a setting-specific approach.

Such legible and estimable feedback variables may actually be common, since there is an incentive for the interactee to provide them. For if the interactee provides legible and estimable feedback variables, a responsive agent, artificial or not, can use these to try and improve its behaviour – which would benefit both the agent *and* the interactee.

This means that using a responsive approach could thus turn finding socially appropriate actions into a joint effort – an interaction. With the interactee actively providing legible and estimable feedback variables, be it consciously and/or subconsciously, and the agent continuously reacting to them (and vice versa).

4.3.2 *The improvement strategy to select better actions*

Another important difference between the responsive and the setting-specific approach is that the former uses an improvement strategy function instead of a (prior) knowledge function. This gives the responsive approach a reduced dependency on knowledge for all setting variables and allows for individualized instead of stereotyped adaptation. We will here argue that, in doing so, the responsive approach can avoid the challenges of defining and implementing a knowledge function, by replacing them with with the fundamentally different challenges of defining and implementing an improvement strategy.

REDUCED DEPENDENCY ON ALL SETTING VARIABLES Since a responsive approach depends only on feedback information, not on a knowledge function on all relevant setting variables, it avoids many of the challenges faced by a setting-specific approach, such as the combinatorial explosion and the challenges of establishing what setting variables are relevant.

In addition, the responsive approach can be scaled up or down depending on the available feedback information. With just a single piece of legible basic feedback, the improvement strategy can be to keep trying until an optimally/sufficiently appropriate action is found; as the available feedback information becomes more rich, so too can the improvement strategy be made more finely attuned to efficiently find optimally/sufficiently appropriate actions.

If the feedback information is not sufficiently legible, a system might combine multiple feedback variables that encode that same feedback information to get a reliable estimate. In these cases a responsive approach could, like the setting-specific approach, face the challenge of needing to estimate a lot of variables to work properly.

INDIVIDUALIZED INSTEAD OF STEREOTYPED ADAPTATION A responsive approach per definition uses the feedback given by individual interactees, rather than working from knowledge generalized to the population of interactants. Since feedback is individual, and responsiveness adapts to those individual preferences, the responsive approach will inherently be individualized. This individualization might even apply to how an interactee prioritizes different attitudes, if this prioritization can be expressed in feedback variables.

This circumvents the stereotyping challenge faced by a setting-specific approach. It also shows that a purely responsive approach could easily miss out on the advantages of such stereotyping. Herein, the two approaches can complement each other. A setting-specific approach could be used to select initial 'stereotyped' actions, that can then be refined into more 'personalized' actions using a responsive approach.

DEFINING AN IMPROVEMENT STRATEGY The responsive approach depends on suitable improvement strategy functions. In contrast to the knowledge function of the setting-specific approach, an improvement strategy can be defined to deliberately use various aspects of the interaction. For example, an improvement strategy could be to directly ask the interactees for the desired actions. Furthermore, interactees might even appreciate the attempts of a responsive agent to try and improve the interaction, regardless of the appropriateness of the selected actions. While introducing such interesting options, this flexibility could also make it a challenge to create suitable improvement strategies.

4.3.3 *Quality of the selected action*

Where a setting-specific approach can ideally aim for selecting the most appropriate action, a responsive approach instead aims for improvement. Consequently, a responsive approach will be most suitable if the cost of selecting an inappropriate action is not too high and/or if no systems exists that reliably deliver the most appropriate action.

In some cases, showing responsive behaviour may actually *be* the appropriate action. That is to say, the mere act of changing ones behaviour after social feedback cues have been given may be perceived as appropriate – at least in the short run. One could even hypothesize that it could occasionally be more important to be responsive than to show appropriate behaviour per se (see Box 6).

4.3.4 *Conclusions*

Unlike a setting-specific approach, a responsive approach does not aim for optimal social appropriateness. There could be some improvement strategies that may find optimal actions[13], but, unless the feedback provides direct information about an optimal action, it logically is unlikely that an improvement strategy can guarantee optimal social appropriateness.

Will it be sufficient if a responsive agent (at best) can only find sufficient or improving actions? The answer to this question clearly depends on the requirements and setting in a particular situation. If an agents knows and can find a socially appropriate action in one go using another approach, it is unlikely that being responsive will add much. But in cases where no approaches are known (yet) to find such an appropriate action in one go, responsiveness may provide an alternative pathway to still finding it.

In addition, since for the first action(s) of a responsive agent no feedback will be available, it is quite likely that in the beginning of an interaction its action(s) may be insufficient. In fact, the first action(s) could even be insufficient to such an extent that they interactee refuses to continue the interaction, e.g. if a robot trying to find an appropriate interaction distance starts by colliding with the interactee. One way to circumvent this challenge would be to use another approach for selecting the first action(s) of an interaction; this could, as we suggested before, well be a setting-specific approach.

Overall, compared to the setting-specific approach, responsiveness can be seen as taking a more online approach to social appropriateness. Where the setting-specific approach tries to encode it in its knowledge function, responsiveness instead tries to detect it from social feedback cues and use it throughout the interaction to improve its actions. As we have argued above, this circumvents the challenge of encoding and applying the knowledge function, while introducing the challenge of detecting and responding to social feedback cues.

13 One example that might actually work in quite a few settings for quite a few actions, would be to directly and pro-actively (verbally) ask the interactees for the desired actions, and then follow the indicated preference. This approach does require the agent to first use the probably not optimally socially appropriate action of asking, which may in some cases be considered inappropriate in itself.

"I just want you to listen"

Within our framework, we have thus far spoken of 'the most appropriate action', but does such an action actually exist? What if the perceived social appropriateness of an action depends on what happened before?

These thoughts suggest a further interactive dynamic within interaction; we continuously influence each other's expectations. We can thus well hypothesize that earlier actions of a robot have an effect on what is considered appropriate behaviour for it later.

It may even be that acknowledging earlier mistakes (as signalled by social feedback cues) is in that way also considered as appropriate. The act of being responsive to a social feedback cue may consequently in itself be perceived as socially appropriate.

We found a range of indirect support for this hypothesis. For example, we have found that failures of a robot best predict an effect of the interaction if we take a memory effect into account (see Box 4). We have also found indicators that a robot that apologizes for and repairs its mistakes is perceived as *more* sensitive than one that does not make those mistakes at all (see Box 7). This idea also seems to be very much in line with our findings in Chapter 7.

Box 6: The dynamics of social appropriateness

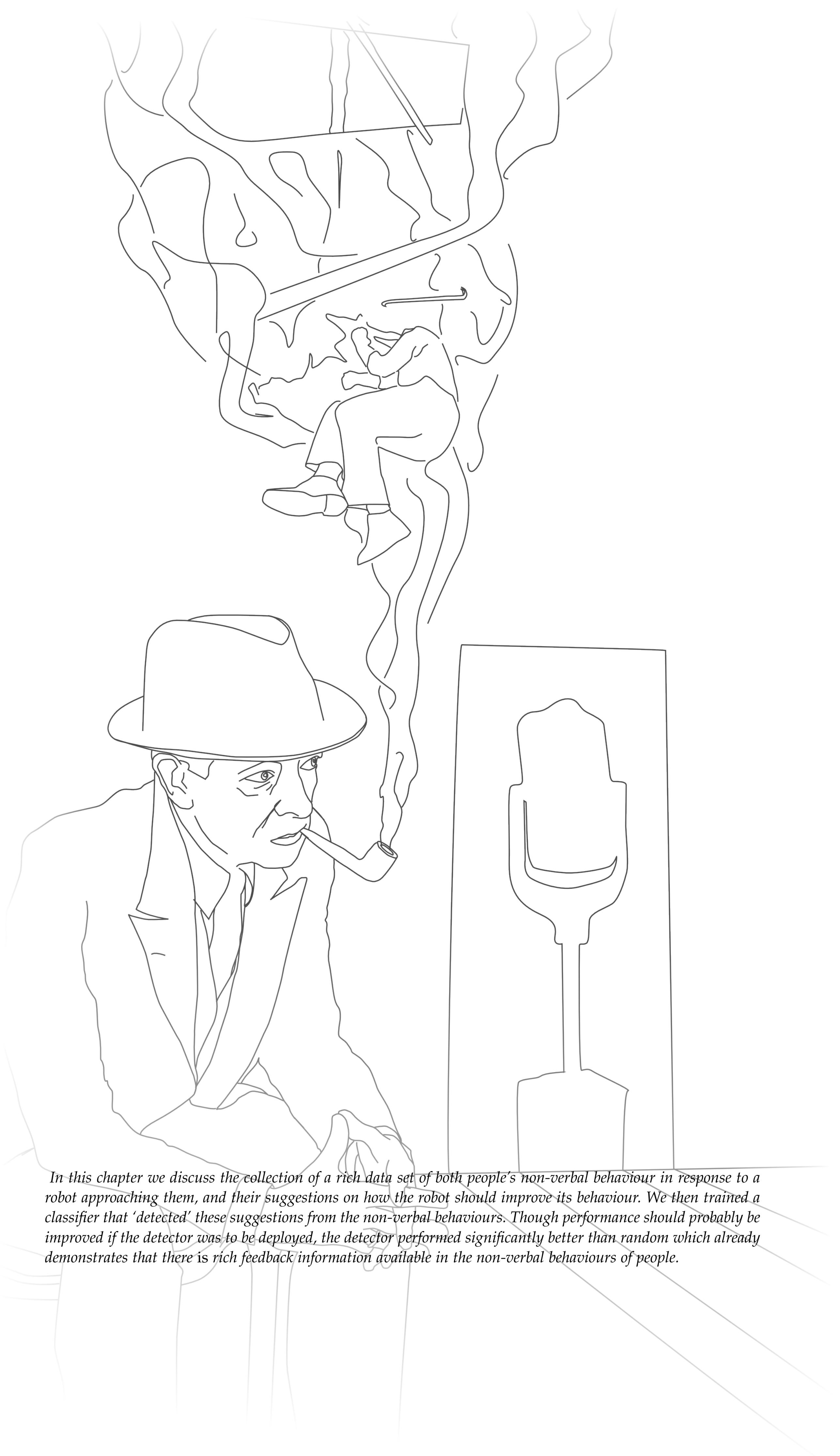
4.4 DISCUSSION

We have given formal definitions of both the responsive and the setting-specific approach. Though in theory capable of finding the optimally appropriate behaviour, the setting-specific approach ideally requires the agent to estimate and reason with all relevant setting variables – which is infeasible in realistic settings. We showed that the responsive approach can be used to (partly) circumvent these challenges, as it instead uses a reactive approach to improve social normativity until it is sufficient/optimal.

Our theoretical discussion of the responsive approach can serve as a starting point for implementations. Crucially it identified the components that would be required for such an implementation; (1) extraction of feedback information from social feedback cues, and (2) the implementation of suitable improvement strategies. Such implementations would further depend on (3) the assumption that people will actually want a (robotic) agent to adapt its behaviours in response to feedback. Since both responsiveness and (online) reinforcement learning need to adapt to feedback, insights from the latter could be applicable to such implementations; forms of (online) reinforcement learning may well be able to implement parts of responsiveness – though for such implementations to be truly responsive, the adapting should explicitly be part of the social dynamic, rather than finite learning.

If suitable implementations can be created, explicitly considering a responsive approach can offer various opportunities. One such opportunity is to complement a setting-specific with a responsive approach. Another opportunity would be to use responsiveness in a more proactive way, for example by directly asking interactees which actions they would prefer. Further opportunities can be found in the improvement strategy, e.g.; (a) with intelligent reasoning about why the agent got particular feedback, it may be able to respond to it more appropriately, or (b) giving responsive agents different personalities by parametrizing the different factors weighed by the agent when adapting to feedback, such as its own needs and those of the interactee.

Overall, we have introduced an explicit definition of responsiveness, and argued for the potential value of the approach. In the following chapters, we will use this definition to explicitly consider its application in (artificial) social agents. Not necessarily as a replacement of the setting-specific approach, but as a potentially valuable addition.



In this chapter we discuss the collection of a rich data set of both people's non-verbal behaviour in response to a robot approaching them, and their suggestions on how the robot should improve its behaviour. We then trained a classifier that 'detected' these suggestions from the non-verbal behaviours. Though performance should probably be improved if the detector was to be deployed, the detector performed significantly better than random which already demonstrates that there is rich feedback information available in the non-verbal behaviours of people.

5 IMPLEMENTING FEEDBACK CUE DETECTORS

What if a robot could detect when you think it got too close to you during its approach?

If the robot detects that you think it got too close, it can move back. If the robot detects that you think it stayed too far away, it can move forward.

As we have argued in the previous chapter, the ability to participate in the dance of responsiveness depends crucially on the ability to detect such feedback. Beyond the framing of responsiveness, we should expect robots to make unintentional mistakes in the diverse contexts of social interaction, and detecting they did so will be a necessary first step in trying to fix such mistakes.

Since attitudes are thoughts/feelings, i.e. internal, we can only detect them if they are somehow reflected in observable behaviour – which can be anything from spoken feedback to non-verbal body language. Following our definitions from the previous chapter, we will here refer to such (non-verbal) observable behaviours that reflect people's attitudes on earlier behaviours as **social feedback cues**, and to those attitudes as **feedback information**. Previous work has used easy-to-detect cues, e.g. the use of estimated subjective task difficulty to try and adapt the difficulty of a learning task [84], and the use of specific non-verbal utterances to guide the adaptive behaviours of a conversational agent [17].

In this chapter we investigate if it is possible to automatically detect feedback information from non-verbal social feedback cues in the context of a robot approaching a person – that is, can we detect from the way in which a person responds to a robot's approach behaviour, how they would like it to behave differently? Literature on human-human interaction has discussed various non-verbal behaviours that could serve as social feedback cues, such as averting gaze and leaning behaviour [18, 70, 73]. Yet, to our knowledge, there is no previous work attempting to automatically detect feedback information on a robot's approach behaviour from social feedback cues. Neither are we aware of any datasets that would allow for such attempts.

To be able to train our detector, we thus first collected a dataset in which a robot would approach people, using a range of approach distances, to provide information through speech. We collected both their response behaviours (through a tracking system) and their attitudes towards the robot's behaviour (through a questionnaire) (Section 5.1). Importantly, we needed our dataset to be such that these perceptions would not depend exclusively on the behaviour of the robot –

otherwise, the detector might be able to achieve a reasonable performance by simply considering the behaviour of the robot, rather than actually detecting the social feedback cues (see Figure 9 for a more in-depth discussion). To this end, we introduced a factor that could not be observed directly from our tracking system; level of environment noise. Half of the participants would interact with the robot under high environment noise, so that the robot would be very hard to understand unless it came very close. Our tests revealed no significant effects of the approach distance and the environment noise on the perception of our participants. This suggested that, as required, perception of the participants did not depend exclusively on the distancing behaviour of the robot. Consequently, we used our dataset to train a detector of social feedback cues – achieving a performance significantly better than chance and identifying various relevant features (Section 5.2). Together, these results suggest that it might be possible to achieve responsive social positioning (Section 5.3).

5.1 A DATASET FOR DETECTING SOCIAL FEEDBACK CUES

This work requires a specific kind of dataset, as we are aiming to detect peoples' opinions of a robot's behaviour, i.e. *their internal state*, from social feedback cues, i.e. *their external non-verbal behaviours*. This poses three demands on our data collection:

1. To ensure a rich and sufficiently diverse dataset, the set-up should elicit a variety of internal states and leave participants free to display external non-verbal behaviours as they please;
2. To ensure that the different data points we would collect could be used in a comparable way, the interaction would have to follow a somewhat controlled pattern;
3. To ensure that our detectors actually need to use the social feedback cues, the internal states should not depend exclusively on observable factors that we manipulated (see Figure 9).

We will in this section discuss our controlled data collection, which was designed to strike a feasible balance between these demands.

Each participant was given the task to solve a murder mystery together with the robot. The robot had the task to collect the clues, which gave it a reason to approach the participant several times (with different interaction distances) in each experimental session. Control of the robot was done by a Wizard of Oz, who also used predefined utterances to promote participants to talk with the robot. Through questionnaires we obtained subjective rankings of participant comfort, and feedback on the behaviour of the robot. We used a tracking system to collect detailed position data on both the participants and the robot.

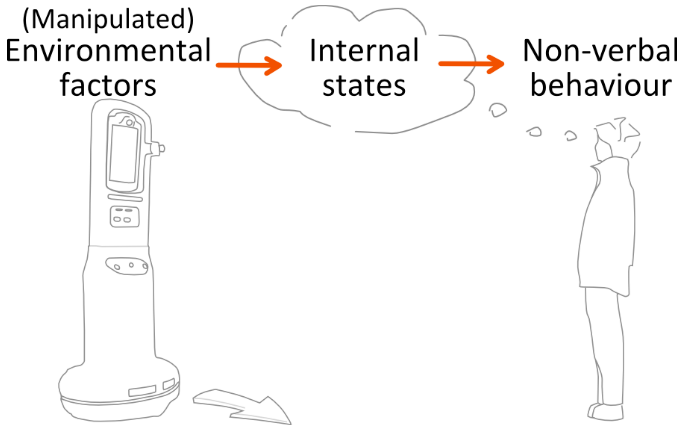


Figure 9: Schematic overview of how (manipulated) environmental factors can influence internal states, which can in turn be reflected in (non-verbal) behaviour. These two relations (represented by arrows) could both be used to detect internal states, provided that enough data is available. Since our focus is explicitly on the detection of internal states from non-verbal behaviour (the right arrow), we should make sure that our detector will not be able to take the short-cut of instead detecting the internal states from the environmental factors.

5.1.1 *Task and context*

> *"I have the first clue. The detective chief inspector sent someone this morning to investigate several calls about suspicious noises from the old neighbourhood. He just reported a homicide.*
>
> *The victim was found in an abandoned school building, with a stab wound in his neck. He seems to have been stabbed from close-by, perhaps from behind. Next to him a crowbar was found, there was no blood on it."*

To allow for the collection of multiple data points, we needed a task and context that would allow for the robot to approach the participants several times in a meaningful way. To this end, we used 'the School case', a murder mystery task used in our earlier data collection (Section 3.2). Within this task, the robot would, in 8 iterations:

1. Approach the participant to give them a clue relevant to the murder mystery;
2. Briefly discuss the clue with the participant;
3. Indicate that it would go collect the next cue, and then retreat from the conversation;
4. (While the robot was retrieving the next clue, the experimenter would come in and give the participant a brief questionnaire on the interaction.)

The clues were designed to all be comparable in length (20-30 seconds long) and information content; each clue would start with some filler text on how the clue was collected, e.g. *"I have the fourth clue. The detective chief inspector had a hunch and also had someone ask around at several hardware stores"*, followed by information relevant to solving the murder mystery, e.g. *"Yesterday, around 6 p.m., the victim visited a local hardware store to purchase a crowbar."* To make the clues similar in length, some clues would end with more filler text, e.g. *"The shop assistant positively identified him."*

After sharing the clue, the robot would maintain a brief conversation about the clue for about 1 minute. To do so, we implemented a simple Wizard of Oz set-up in which an experimenter could select and play various pre-recorded audio files. Beyond the clues, these fit two categories. Firstly, there were simple answers to questions the participants might ask, e.g. *"Yes"*, *"No"*, *"I did not catch that"*, *"I do not know"*. The experimenter was instructed to avoid giving opinions and to only give information that was also available in the clues shared thus far with the participants. Secondly, we included questions to engage participants in the murder mystery, e.g. *"What do you think happened?"*, *"Why?"*, *"Do you already have a suspect in mind?"*, *"Can you elaborate?"*.

After the brief conversation, the robot would wrap up the conversation by saying *"I will now go and collect the next clue,"* after which it would do so. Each participant would in this way be presented with a total of 8 clues, which together provided enough information to solve the murder mystery. After that, the robot would approach them a 9th time, and ask them whom they suspected. This 9th approach was mainly included to allow participants to wrap up their interaction with the robot. It deviated from the other interactions in that it did not end with the robot retreating after about one minute, but instead with the experimenter ending the interaction after the participants had discussed their main suspect. For this reason, this approach was excluded from our analysis.

5.1.2 *Data collection*

Throughout the experiment, we tracked the position of our participants and made video recordings of the interaction. In between each interaction with the robot, the experimenter would present participants with a between-session questionnaire, and after participants had gone through all interactions we presented them with a post-experiment questionnaire.

As discussed before, we needed to strike a balance between allowing our participants to move and react freely, while also keeping the collected data comparable. To this end we used three cover stories. Firstly, we told participants that all equipment used in the data collection was intended for autonomous robot behaviour. This reinforced the idea that the robot was autonomous, while also serving to make the participants less aware of their actions and reactions being recorded. Secondly, we wanted to ensure that participants would be forced to let the robot approach them, and not the other way around. To not make the participants explicitly aware of their own social positioning behaviour, and possibly influence it, we wanted to avoid asking them to behave in a particular way. Instead, we used a wired skin conductance measuring device – the wire, connected to the participants' left hand, effectively limited their movement range to the wire's length (approximately 1 meter) around the device. Thirdly, when handing the participants the between-session questionnaires, the experimenter would always do so from the same position. This served as a means to roughly (and softly) 'reset' the position of the participants in between each approach. All participants were, of course, debriefed after the experiment about the deception involved in these cover stories.

5.1.2.1 *Objective measures*

To track the position of our participants, we equipped them with two uniquely identifiable markers. One marker was worn on the back of the chest, with two straps going around the shoulders. The other marker was worn on a cap. This provided us with separate tracking of head and torso, which allowed us to look into the behaviour of the participant with more detail. The robot was similarly equipped with markers. All markers were tracked by an OptiTrack (`www.naturalpoint.com/optitrack`) motion capture system using 12 infra-red cameras. This set-up allowed for sub-centimetre level precision tracking of both position and orientation of each marker.

In addition, we also recorded the whole interaction with a video camera. While we also equipped participants with the sensors to measure their skin conductance, with the idea that this would provide a physiological measure of discomfort, the resulting data was discarded as it turned out that we did not reliably get measurements in this setting where participants could move around.

5.1.2.2 *In-between questionnaire*

After each interaction with the robot, we asked participants to answer nine short questions about that interaction. Specifically, we asked participants how comfortable they were with the behaviour of the robot (sliding scale, 1-100) and to rate the robot as being intelligent, sensitive, pleasant, and thorough (7-point Likert scale, Not at all (1) - Very much (7)). To keep participants focused on the task, we also asked them how relevant the latest clue was towards solving the case. Lastly, we asked participants to suggest changes to the robot's behaviour; on a 7-point scale they could indicate desired changes to positioning behaviour (The robot should... get much closer - not change its position - stay much further away) and, similarly, to its volume settings (The robot should... increase its volume - not change its volume - decrease its volume). We concluded each in-between questionnaire with an open question in which participants could give other suggestions for improvement.

The 9th interaction was different from the others, in that the robot would not present a clue, but would instead ask the participants to indicate whom they suspected and then let them answer without retreating from the interaction. We here presented them with the same in-between questionnaire, but swapped out the question on the relevance of the clue for an (open) question on whom they suspected to have committed the murder.

5.1.2.3 *Post-experiment questionnaire*

After the experiment was over, we asked the participants for demographic information. Specifically, we asked for gender, age, education, country of origin, history of pet ownership [91], and prior experience with robots. In addition, given our manipulation of environment noise, we checked participants' hearing loss, and asked participants to indicate how they experienced the noise level in the lab (7-point Likert scale, no noise at all (1) - a lot of noise (7)).

5.1.3 *Conditions*

As discussed above, we introduced two factors in this data collection; within-subject we manipulated the interaction distance the robot would use during its approach, while between-subject we manipulated the environment noise.

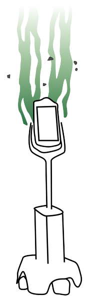
5.1.3.1 *Interaction distance*

Approach distance of the robot was manipulated within-subject, using the distances 30cm, 70cm, 110cm, and 150cm (measured from head-to-head, in the floorplane). These distances were chosen to be evenly distributed, while falling into four distinct informal social interaction distance classifications of Hall [31, p.126]; not close intimate, close personal, not close personal, and close social, respectively. These distances also align with literature in HRI, where, for human-sized mobile robots, distances around 30cm are often found as well invading personal space (e.g. [13, 43, 91, 104]). Furthermore, as the robot could only be controlled with limited precision, these distances were chosen such that even with those minor deviations they would still be distinguishable.

We used each approach distance twice, resulting in a total of 8 data points per participant. To counteract order and sequential effects, we used an 8×8 balanced latin square design to counterbalance.

For practical and safety reasons, the approach behaviour of the robot was controlled by the experimenter using a Wizard-of-Oz approach.

5.1.3.2 *Environment noise*



For our other condition, we aimed to find a between-subject factor that would effectively influence participants' perception of different approach behaviours, without being directly observable from the tracking data recorded.

In a variety of small pilots and pre-studies we tried out different such factors. Smell seemed a good candidate, but turned out to be hard to reliably tie to the robot; participants would be aware of the presence of the smell, but did not seem to relate it to the robot or its approach distance. We used ammonia to create the smell, but found that it lingered too long and started pervading the whole space, which could explain why participants did not relate it to the robot, nor to its approach distance. We also tried two more psychological manipulations of framing, team membership (following e.g. [71]) and perception of the robot as safe/unsafe, in a simple stop task – the robot would approach participants, and they would tell it to 'STOP' when they perceived it to be at a comfortable interaction distance. In both pilots we found big individual differences in stop distances (ranging from 15cm-195cm), but we saw no indication that these differences were caused by our manipulation of team membership and/or perception of the robot as safe/unsafe.

In the end we settled on environment noise as a factor, as it seemed most suitable. Previous work has suggested that perceptual challenges may be related to proxemic preferences in interactions with robots [67, 68, 102]. This also aligns with Hall's work, who explicitly tied his informal social interaction distance classification to different perceptual qualities [31] (this was also one reason we tried smell). We conducted a simple stop task with high/low environment noise as a small pilot (n=12), which we deliberately framed in the context of having a conversation with the robot. While we still found relatively big individual differences in stop distances (ranging from 5cm-95cm), the data suggested, in line with what previous work would suggest, a clear effect of high/low environment noise on stop distance.

To implement our manipulation of environment noise, we hid 4 speakers above the drop ceiling of the experiment room and played white noise from them. In the low condition, we set it to a low volume such that it was audible but not invasive – sounding akin to the noises made by some air conditioning systems. In the high condition, we set it to the highest volume, such that to the experimenter it was challenging to follow the robots' speech if it was about 100cm away.

We started the white noise before the participants would enter the experiment room, apologizing for it if participants asked about it without suggesting it pertained to the experiment. The majority of participants in the high noise condition did ask about it, while none in the low condition did so. Participants were debriefed about this afterwards.

5.1.4 *Procedure*

Participants came in, received a briefing, and read and signed an informed consent form. After that we equipped them with the markers, under the ruse that those markers would help the robot to navigate autonomously. We also hooked them up to the sensors for measuring skin conductance – which forced them to stay relatively close to the measurement tool.

They were then instructed on the task: Solve a murder mystery, the robot will go collect the cues. We told participants that the aim of the study was for them to collaborate with the robot and we encouraged them to talk with the robot, while warning them that its capacities for natural speech were limited. We further instructed them that each time the robot would go collect the next clue, the participants would be presented with a brief questionnaire (presented on a tablet). Just before the interaction started, we started the data collection and conducted a brief calibration.

Then, as described (Section 5.1.1), participants went through 8 iterations in which the robot would present a clue and then discuss it with the participants. To wrap up the interaction with the participants, the robot made a 9th approach in which it asked participants to point out their main suspect and indicate why they suspect them.

After the interaction with the robot was completed, participants were asked to fill in the post-experiment questionnaire. After the experiment was over, participants were debriefed fully and were offered a small fee to thank them for their efforts (€6.-).

5.1.5 *Materials*

For our data collection, we used the hardware of a Giraff telepresence robot. However, rather than using it as a telepresence robot, we modified it to show two animated eyes on its screen which would occassionally blink. We prepared a Wizard-of-Oz set-up which allowed for the experimenter controlling the robot to quickly and efficiently select and play pre-recorded audio files on the robot. The experimenter controlled the robot from a laptop, located in a screened off location nearby.

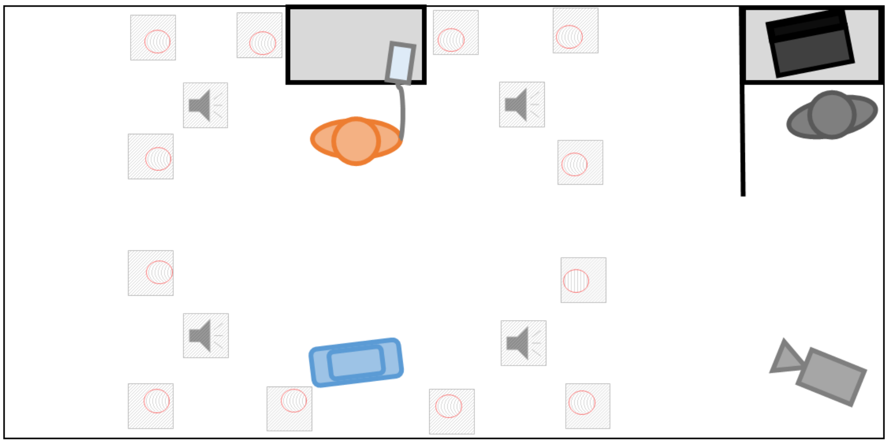


Figure 10: Overview of the experiment room, showing the Wizard-of-Oz set-up with the experimenter (top-right), and the interaction between the participant and the robot (middle). Behind the participant was a table with a device for measuring skin conductance, to which they were connected through a wire. The overview also shows the location of the video camera (bottom-right). Located on and just below the drop ceiling were the infrared cameras (hatched squares with circle) and the speakers (hatched square with speaker icon).

Questionnaires were taken digitally on a tablet, which was presented at the appropriate times by the experimenter. After the participant had finished filling in the questionnaire, the experimenter would take back the tablet, hide behind the screen, and then continue the data collection. The experiment room was equipped with 12 infra-red cameras (part of the OptiTrack system) and a regular video camera for our data collection. See Figure 10 for an overview of the experiment room.

5.1.6 *Participants*

A total of 30 participants joined in our data collection. Of these, 21 (70%) identified as male, the other 9 as female. Most were students, with ages between 17 and 27 (mean age 21.73). The majority (73%) of our participants had the Netherlands as their country of origin. In our other demographic questions, we saw many participants who had ever owned or taken care of a pet (83%), and a fair distribution of prior experience with robots (2 with no prior experience, 14 who had seen robots before, 9 who had interacted with robots before, and 5 who had worked with or programmed robots before).

None of our participants ever wore a hearing aid, and a great majority did not feel they had a hearing loss (90%), nor did their friends or family think they had a hearing loss (90%). One participants rated their hearing as poor, while the rest rated it as fair (4 participants) or better.

5.1.7 *Testing for effects of approach distance and environment noise on perception*

The controlled data we collected can be seen as an experiment testing for the single and joint effects of approach distance and environment noise on perception. Within the context of this work, our main goal was to ensure that perception of the robot's behaviour would not depend exclusively on the approach distance.

As mentioned before, we found no significant effect of either of our manipulations on our measures, in contrast to what we would have expected. In this section we will briefly discuss the research question and hypotheses that guided our analysis, the results, and the implications of those results.

RESEARCH QUESTION In our data collection set-up, we had two manipulations (approach distance and environment noise) and one main subjective measure (the in-between questionnaires). The questions in that subjective measure, the in-between questionnaires, reflected aspects of the way in which participants could perceive the robot. As such, we defined the following research question;

What are the (interaction) effects of approach distance and environment noise on the way a robot is perceived?

Our main interest in this question was to ensure that perception of the robot would not exclusively depend on its used approach distance (Figure 9). In addition, if we had found environment noise to have an effect, it would have been an additional piece of evidence within the relatively small body of literature on the effect of perceptual needs on proxemic preferences in human-robot interaction.

As discussed in Section 5.1.3, both our conditions were chosen because, based on the literature, we would expect them to have an effect. This was further confirmed by our last (small) pilot, where we found that, in a stop task, environment noise did seem to have an influence on preferred approach distance.

RESULTS A principal component analysis (PCA) was run on the 8 items of the in-between questionnaires. Inspection of the correlation matrix showed that the question about the relevance of the clue had no correlations with the other questions greater than 0.3, which is not surprising as it was primarily included to check that the relevance of the clue would not influence our measures; that question was excluded from further analysis. Sampling adequacy was reasonable (Overall Kaier-Meyer-Olkin of .779), though individual measures for the items on the robot changing its position (.442) and its volume (.547) were low. When these items were recoded to a scale from 'strong change suggested' to 'no change suggested', these individual measures improved (to .541 and .559 respectively, with overall Kaier-Meyer-Olkin .774). Data was likely factorizable (Bartlett's test of sphericity, $p<.0005$).

PCA revealed two components that had eigenvalues greater than one and which together explained 68.0% of variance (48.4% and 19.6%). The first component had strong loadings of the questions intended to measure perception of the robot (Comfortable, Intelligent, Sensitive, Pleasant, Thorough), while the second component had strong loadings of the two questions about the robot changing its position and its volume. We will use the component-based averaged scores for these components, labelled as 'Perception' and 'Suggested improvement'.

We conducted a two-way mixed ANOVA to investigate the single and joint effects of approach distance and environment noise on Perception and Suggested improvement.

For Perception, there was no significant interaction between our conditions ($F(3,78)=.306$, $p=.821$). Therefore, we looked into the main effects, but found no significant effects of either approach distance ($F(3,78)=1.357$, $p=.262$) or environment noise ($F(1,26)=.161$, $p=.691$).

For Suggested improvement, there was no significant interaction between our conditions either ($F(3,78)=1.100$, $p=.343$). Therefore, we looked into the main effects, but again found no significant effects of either approach distance ($F(3,78)=1.851$, $p=.165$) or environment noise ($F(1,26)=2.805$, $p=.106$).

Conclusions and discussion These results show that, in this particular dataset, there is no strong effect of approach distance and/or environment noise on perception of our participants.

We want to here speculate about one possible explanation; a key difference between this study and much of the previous work on social positioning, is that we explicitly allowed our participants to move in response to the behaviours of the robot. In other words, it might be that being able to adapt your own position can alleviate the effects of a robot's distancing on the perception of people. This also aligns with our findings in earlier work, where we also allowed participants to move around, and also found no significant effect of approach distance on perception of the robot (see Section 3.2).

5.2 Detecting social feedback cues

As discussed in the introduction, we wanted to investigate if it would be possible to detect from someone's non-verbal behaviour (the social feedback cues) if they thought a robot should get closer or stay further away during its approach (feedback information). Beyond that, we wanted to investigate which features of those non-verbal behaviours would be effective for such detection. To this end, we tried to implement an effective classifier.

Within the scope of this chapter, implementing an effective classifier is a means, not an end. In other words, we are and were not aiming for "perfect scores" and one should not expect them, as we are trying to read peoples' inner thoughts from a relatively small dataset. Instead, we have searched for relevant insights about what factors would play a role in developing and optimizing feature selection for such a classifier. For this reason, we focused on feature selection, and used a standard random forest classifier[1] with 500 trees as our classifier without further tuning.

We will in this section discuss how from the raw data we derived a wide range of features and our labels (Section 5.2.1), and then tried to find which features were relevant for a classifier (Section 5.2.2).

At first we tried automatic feature selection, which mostly failed to reliably select suitable features (Section 5.2.2.1). We have, nonetheless, reported on these efforts, as they might be used to guide future endeavours to the same end. Since our findings suggested that suitable features *did* exist, even though our automatic feature selection failed to reliably select them, we then also investigated the performance with a set of features that had been found to be 'successful', which yielded a performance that was reasonably good (Section 5.2.2.2).

5.2.1 *Data preparation and feature extraction*

From our data collection, we ended up with relatively clean data. The OptiTrack gave us temporal data on position (x,y,z) and 3D orientation (quaternion) for the four markers we used: participant head, participant body, robot head, and robot body. From the in-between questionnaires we further had a measure of participants' perception of the robot for each interaction (8 per participant). We used the questionnaire data to derive our labels (5.2.1.1) and the tracking data to derive our features (5.2.1.2).

5.2.1.1 *Labels*

Since our goal is to detect how participants think the robot should improve its behaviour, the labels we use should reflect this. The participants' answer to the question on how the robot should change its positioning does that, making it a suitable candidate. It has the additional benefit of directly reflecting participants' opinion, in contrast to the two constructs we *derived* from the questionnaire (Perception and Suggested improvement, Section 5.1.7).

1 The classifier and feature selection were implemented using the scikit-learn v0.19.1 toolkit

To limit the number of classes, we translated the 7-point scale of our measures into three bins, encoding qualitatively different feedback information. For the question on how the robot should change its position, these bins were 1-3 'get closer', 4 'don't change position', and 5-7 'stay further away'. These bins resulted in a uneven distribution of the classes, with 'get closer' and 'don't change position' being chosen about equally often, and 'stay further away' being chosen roughly twice as often.

5.2.1.2 *Features*

Even though we only tracked four markers, there are already many different aspects that could be relevant. These include different relations that could exist between markers (we will focus on distance and orientation, following the literature), different time-windows that we could consider around the end of the approach, and different ways of combining these measures in a way that takes temporal aspects into account.

We deliberately computed an exhaustive set of features with all combinations of these aspects, rather than making assumptions on which features to pick. The downside hereof was that it resulted in 4410 features, which is excessive for this small a dataset and thus necessitated the use of feature selection. At the same time, this had the advantage that said feature selection could potentially provide us with information on which features were effective for our classifier.

RELATIONS BETWEEN MARKERS When looking at the relations between markers from which relevant features could be derived, we chose to go with distance and orientation. These are easy-to-compute and intuitively carry a lot of information about the relation between two markers. Moreover, distance and orientation are often discussed as social cues in social positioning in literature on human-human interactions [18].

Since distance is a metric that can be computed in both a two-dimensional and a three-dimensional plane, we used a few variants of distance. Firstly, we used three-dimensional euclidean distance between two markers. Secondly, we used distance as calculated in the doorplane – as if seen from a side view (see Figure 11). Thirdly, we used distance as calculated in the floorplane – as if seen from above.

If we want to reduce an orientation to a single number, an angle, we have to reduce it to a two-dimensional plane. In addition, we are interested in relations, so we do not want to use absolute orientations. We approached this as follows. Representing the orientation of a marker as a vector originating in the position of that marker, and using a second vector from the position of that marker to another marker, we calculated the orientation as the angle between those two vectors projected onto either the doorplane (see Figure 11) or the floorplane.

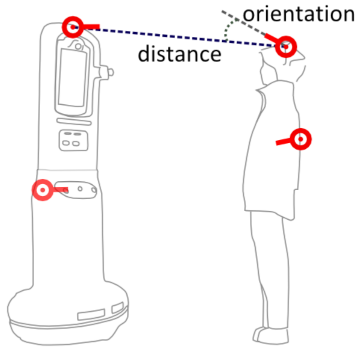


Figure 11: From the markers (shown as circles with a dot for their position and a line for their rotation) we can derive their relative distances and orientations. Here illustrated from a side view, i.e. calculated in the doorplane, but can similarly be applied to a top down view, i.e. calculated in the floorplane.

For each pair of markers, we computed the orientation both from one marker to the other, and vice versa.

In addition, we made a choice regarding the pairs of markers between which we would calculate the distance and orientation. Since the robot made only very limited motions with its 'head' (small tilts to face the participants), we decided to reduce the number of features by not pairing the robot-head with the participant-body and vice versa. As we were interested in the participants' behaviour, we also excluded the pairing of robot-head with robot-body. That left us with three marker pairs; (robot-head, participant-head), (robot-body, participant-body), and (participant-head, participant-body). This last pair, comparing the two markers worn by the participant, yielded other features that are often mentioned in literature as social cues, such as gaze aversion and leaning behaviour [18, 70, 73].

RELEVANT TIME-WINDOWS Given that we had rich temporal data, we needed to select relevant time-windows

As our temporal point of reference, we used the end of the robot approach. This had the practical benefit that it was easily and reliably derivable from the robot reducing its speed to zero (we did this automatically, using an over-sensitive metric and then manually removing the false positives and checking the outcomes). Based on observations in this and earlier studies it also seems a meaningful point for our participants

We then used a range of time-windows around this point in the range [-5s, -3s, -1s, 0s, +1s, +3s, +5s]. Including only time-windows that went forward in time, this yielded 21 time-windows, such as, for example (-5s, -1s), (-1s, 0s), (-3s, +3s). We used this range of time-windows to ensure that we could get insights in both 'reactions' that were more preparatory and 'reactions' that were more reactive. Additionally, we were interested to see if, and to what extent, it might be possible to detect peoples' perception of a robot's approach *before* the robot would actually complete that approach.

COMBINING TEMPORAL MEASURES INTO FEATURES Given that we used functions to compare two markers (based on distance and orientation), there are various ways in which we can use those functions within the time-windows we defined.

For this, we used four different methods:

[single moment] Apply the function to the two markers on the first time-marker, ignoring the second time-marker. Return the outcome.

[difference] Apply the function to the two markers on the first time-marker and on the second time-marker. Then return the difference between the two outcomes.

[time-compare] Apply the function to the marker on the first time-marker and the marker on the second time-marker, ignoring the second marker. Return the outcome. We excluded time-compares of just the markers on the robot, as we were primarily interested in the reactions of the participant.

[merge] Apply the function to the two markers for each time-stamp in the time-range. Use a merge-function to compute a single return value from this array of outcome. We used several merge-functions; average, standard-deviation, minimum, and maximum. Additionally, we used those same merge-functions on an array derived from the array of outcomes, containing the difference between each outcome and the next. As such, this derived array represented the rate of change (i.e. speed).

Given these methods, we combined all these different aspects into a large set of computed features. These features captured a wide range of aspects of the interaction that could potentially serve as a social cue, from 'distance (3D) between the participant-head and the robot-head at the end of the approach (0s)' to 'average orientation (doorplane) of participant-head to robot-head in the 3 seconds after the approach (0s, +3s)'. For 7 distance and orientation functions, for 3 pairs of markers, for 21 time-windows, and these 11 distinct methods to combine them, this resulted in a total of 4410 such features[2].

5.2.2 *Feature selection*

After generating this many features, our next step was to perform suitable feature selection. At first, we used a combination of fea-

2 $7 \times 3 \times 21 \times 11 = 4831$, minus the duplicate features resulting from ignoring the second time-marker for single moment features ($7 \times 3 \times 14$) and ignoring the second marker for time-compare features ($7 \times 1 \times 21$)

ture pre-selection based on a variance threshold, selection of features having the highest chi-squared scores, and feature selection based on average gini-importance in a random forest. Initial results on a participant-independent training set and test set seemed barely above chance level, which improved to a very small but significant difference on a participant-dependent training set and test set. Performance in both cases had a very high variance, which suggested that there were meaningful features to be found, but the feature selection had difficulty finding them. We confirmed this by using a set of features that was successful in one of the training folds and showing that, without further tuning, these features significantly improved performance on the participant-dependent test set.

5.2.2.1 *Automatic feature selection*

Our dataset consisted of 240 (30 participants $\times$ 8 interactions) data points, with for each data point 4410 features and 1 label. This dataset was split in a train and a test set, further reducing the number of data points available for training. As such, our dataset is relatively small and any classifier is likely prone to overfitting. These challenges motivated our decision for which classification procedure to use.

Firstly, we chose to use two forms of feature selection, to reduce the number of available features and reduce the risk of overfitting. We used a chi-squared score based method to pre-select a subset of k features with the highest scores, after a pre-selection based on variance threshold (cutoff at .8). We then further selected from these features, by training a random forest with n trees, and then selecting features that had a gini-importance higher than $1/k$[3].

For completeness, we tested four cases; no feature selection, only chi-squared score based feature selection, both forms of feature selection mentioned above, and manual feature selection. The latter, manual feature selection, was added as an alternative and had resulted in a selection of 8 features together representing stepping away, leaning away, and averting gaze in the (0,+1s) and (-1s,+3s) time frames. Using only random forest based feature selection (without chi-squared score based feature selection) was not included as a case as it is ineffective; with 4410 features, gini-importance of each individual feature would become so low that selection based on those gini-importances would be too sensitive to noise.

Secondly, as we were interested in the relevance of the different time-windows to the performance of the classifier, we also manipulated the time-windows that would be included in the dataset. Introducing t, as a variable taking one of the moments [-3s, -1s, 0s, +1s, +3s,

3 Since the sum of gini-importances over all features for a random forest is equal to 1, and k is the number of features used, this method selects all features that had a higher gini-importance than could be expected based on chance.

+5s], we would only include features in the dataset that had values for time-windows up to and preceding that moment.

Together, this introduced several hyper-parameters that we wanted to investigate; k (number of features from pre-selection), n (number of trees used), t (included time-windows), and type(s) of feature selection to use. For this we used cross validation within the training set.

PARTICIPANT-INDEPENDENT CLASSIFICATION We first tried to train a participant-independent classifier. That is, we split the dataset into a training set and a test set, such that all data points of a participant were in the same set. We similarly separated validation sets from the training set for our cross validation. This ensured that the classifier would always be tested with data points from a participant it had not been trained on – which would mean that, in the case of a good performance, our findings would likely be easily generalizable to new and previously unseen people. We wanted to avoid too large an influence of outlier participants, and thus split the dataset in 5 parts of 6 randomly chosen participants each; one formed the test set, the others the folds in the training set (4-fold cross-validation).

Already in our cross-validation, we saw that performance mostly was barely above chance-level[4] – despite feature selection, and across all hyper-parameters. To our surprise, performance on the training set was consistently near-perfect, while performance on the validate-set would drop to chance-levels. This seemed to be partly due to the curse of dimensionality – without feature selection, performance barely increased even when we included the correct label as a feature, demonstrating that the algorithm was unable to identify relevant features from a feature set of this size. However, even with small feature sets, we still had similar results.

We investigated several alternatives, trying to challenge our assumptions, but found no increase in performance. Firstly, we investigated our choice for the labels, by also testing with labels derived from binning participants' score on Perception and Suggested improvement (see Section 5.1.7) – this did not seem to affect performance. Secondly, we investigated our choice for the random forest classifier. We tried several other classifiers (Naive Bayes, Support Vector Machines), but to no avail. We also tried further tuning of other parameters of the random forest classifier, aiming to make it less susceptible to overfitting to our feature set: trying several different numbers for the maximum number of features used by each tree, enforcing a maximum depth for the trees, and increasing the number of samples that

4 It is worth noting that performance for a t of -3s was especially low, being consistently below chance-level with an overall average precision of .262. This does make intuitive sense, as in that time-window the robot would have barely started its approach, thus providing participants with little to no reason to already judge the appropriateness of the robot's behaviour.

were required to split an internal node. Again, this did not seem to affect performance in our cross-validation.

Since all these alternatives failed, the most likely explanation seemed to be that aspects of individual participants *did* matter and should be taken into account.

PARTICIPANT-DEPENDENT CLASSIFICATION As we suspected that aspects of individual participants played an important role, based on our first attempt discussed above, we then tried participant-dependent classification. To do so, we split the dataset in a train (200 data points) and test set (40 data points) such that the data points of individual participants were spread across these two sets. We similarly separated validation sets from the training set for our cross validation, creating 5 folds with 40 data points each. This ensured that our classifier would usually have encountered a few data points from each participant in its training set before validation and testing. In our initial tests, we found that this already seemed to improve performance a bit, even without feature selection (average precision of .433 on the training set), and we thus investigated this more in-depth.

We then ran our full cross-validation, to find a hyperparameter setting where average performance was high and stable in terms of standard deviation and average performance with similar hyperparameter settings. Of the two peaks found, the peak around t=-1, k=10, and n=5000 (average precision of .462 with standard deviation .068) was discarded as standard deviations for those values were relatively high. We thus chose to go with feature selection based on both chi-squaredscore (k=45) and gini-importance in a random forest (n=100) for time frames up to t=0 (average precision of .452 with standard deviation of .038, and similarly low standard deviations for similar hyperparameters).

We trained our classifier on the full training set, with feature selection using the found hyperparameter settings, and then tested its performance on the test set (holdout validation). This resulted in an average precision of .38 on the test set.

As this is but a small improvement relative to what would be expected of a random classifier with three classes, we further wanted to investigate if performance was consistently better than random. To ensure a fair comparison, we used the expected precision of a random classifier that would take into account the relative frequencies of the different classes in the training set – which, given the distribution of labels in our dataset resulted in a performance slightly better than pure random. For this comparison, we used repeated holdout validation. We took the full dataset and split it into different random train and test sets. On these splits, using the found hyperparameter settings, we then trained and tested our classifier. We repeated this a total of 20 times to get a reasonable sample. For each of these splits, we also computed the expected value of the random classifier. To compare the outcomes, we ran a one-tailed Wilcoxon signed-rank test, which showed a very small but significant increase in average precision between our trained classifier (median of .391) and the random classifier (median of .376), Z=1.792, p=.037.

While we thus found a small but significant improvement of our trained classifiers, it is worth noting that the variance of the trained classifiers was much higher than that in the random classifier, with standard deviations of .064 and .016, respectively. As performance improved upon random, we can conclude that features do contain (some) information on the labels. At the same time, the small difference and the high standard deviations strongly suggest that our current automatic feature selection cannot yet reliably find these features.

5.2.2.2 *Classification with a successful set of features*

Based on our findings with automatic feature selection we expected that suitable features existed and were occasionally but unreliably found by our automatic feature selection. To investigate this, we tried how effective classification would be if we used a set of features that had been found to be 'successful'.

To find a set of supposedly suitable features, we looked into the features that were found during automatic feature selection. Specifically, we selected features by using those from the (outlier) highest-performing classifier in one of the train folds (participant dependent, using all types of feature selection with t=3,k=10,n=50), with a precision of .609. Cross-validation of these features on the other folds in the training set also seemed promising, with an average precision of .394. An overview of these four features can be found in Table 10.

As these features were selected based on (their performance on) the participant-dependent training set, they can be tested on the participant-dependent test set, but not on the participant-independent test set. With this constraint in mind, this approach can still show us if indeed suitable features exist, by testing if classification with these features is successful.

We will here discuss these features and the performance of our classifier using these features on the participant-dependent test set.

INTERPRETING THE FOUND FEATURES What do the four used features entail? We will here discuss the kind of movement they encode and the ways in which those movements *might* be related to participants' perception of the robot. These theories are only hypotheses; further work will be necessary to investigate our interpretations, and to see if and how these features generalize.

[Difference(-5,-3) ***in*** **Distance(3D)** ***between*** **(participant-head, robot-head)]** The distance (3D) between the participants' heads and that of

Combiner	Time window	Relation	Marker pair	*Average gini-importance*
Difference	(-5,-3)	Distance (3D)	(participant-head, robot-head)	*.263*
Maximum difference	(-3, 0)	Orientation (Doorplane)	(robot-body, participant-body)	*.232*
Maximum difference	(-3, 0)	Orientation (Floorplane)	(robot-head, participant-head)	*.260*
Difference	(-5,+1)	Distance (Doorplane)	(participant-head, participant-body)	*.244*

Table 10: Overview of the features used by our evaluated classifier, and the classifiers used in the cross-evaluation. As an indicator of their (relative) importance we have given their average gini-importance in the classifiers used in the cross-evaluation.

the robot can readily be interpreted as focusing on interpersonal distance, and seems directly related to our manipulation of robot approach distance. But why would it be relevant to look at interpersonal distance in this particular time window, 3 seconds before the end of the approach? Our best guess would be that this might represent some sort of anticipation or prior impression of the robot – possibly based on the earlier interactions within the data collection. Alternatively, or additionally, this feature might also be representative of approach speed.

[Maximum difference(-3, 0) ***in*** **Orientation(Doorplane)** ***between*** **(robot-body, participant-body)]** The maximum speed of the orientation in the doorplane would encode the abruptness of position changes in either the robot or the participant, with higher values if the robot is closer to the participant during such changes. As such, it could be suitable as a very specific measure of the abruptness with which participants step away from or closer to the robot.

[Maximum difference(-3, 0) ***in*** **Orientation(Floorplane)** ***between*** **(robot-head, participant-head)]** While very similar to the previous feature, this feature looks instead at the floorplane and would thus specifically encode the abruptness of side-ways position changes in either the robot or the participant. It also looks at the participants' heads, rather than at their body. Based on inspection of the videos, this feature might well represent participants stepping towards the robot and turning their heads, aiming one of their ears towards the robot – presumably in an attempt to better hear the robot.

[Difference(-5,+1) ***in*** **Distance (Doorplane)** ***between*** **(participant-head, participant-body)]** The distance between participants' heads and bodies would encode all kinds of lengthening and shortening of the spine – i.e. leaning behaviour. This could be forward folding (flexion), back/neck bending (extension), lengthening (axial extension), and possibly also shoulder movement (as the body-marker was worn on the back with backpack-like straps going over the shoulders). Since this feature looks specifically at the doorplane, this would likely be leaning behaviours towards or away from the robot. We hypothesize that the first measure, at 5 seconds before the end of the approach, encodes a baseline, compared to which the second, at 1 second after the end of the approach, indicates if the approach made participants lean more or less away from or towards the robot.

PERFORMANCE ON THE TEST SET Since we found these features based on their performance within one fold of the participant-dependent training set, we needed to test them on the participant-dependent test set as well.

Performance on the test set was reasonably good (see Table 11), and better than what we had previously found with automatic feature selection. Performance on the individual classes aligned with their frequency in the train and test set, with performance on 'stay further away' being higher than performance on 'not change its position', which in turn was higher than performance on 'get closer'. The latter performs below chance level, which seems to indicate that our classifier mainly works well for detecting when our robot was perceived as staying too far away.

We further investigated if performance was significantly better than what would be expected of a random classifier taking into account the relative frequencies of the different classes. As before, we used repeated holdout validation, splitting the full dataset into different random train and test sets, on which we then trained and tested our classifier with the chosen features. We repeated this a total of 20 times and then compared against the expected value of the random classifier. To compare the outcomes, we ran a one-tailed Wilcoxon signed-rank test, which showed a significant increase in average precision between our trained classifier (median of .483) and the random classifier (median of .366), $Z=3.360$, $p=.001$.

Overall, these findings show that in a participant-dependent case there are indeed social feedback cues that a robot might use to detect if people think it chose an appropriate interaction distance. As noted before, our approach in selecting these features here does not allow for generalizations to a participant-independent case.

5.3 CONCLUSIONS AND DISCUSSION

In many senses, this chapter has been a (chronological) report of our more and less successful attempts to detect the appropriateness of a robot's social positioning behaviour from non-verbal cues. We started by collecting an extensive dataset, manipulating approach distance and environment noise, measuring the perceived appropriateness, and tracking temporal positioning information. As this dataset had two conditions, approach distance and environment noise, we tested to see if these had an effect on perceived appropriateness. These tests revealed no significant single or joint effects, which we have hypothe-

	The robot should...			*Average*
	get closer	not change its position	stay further away	
Precision	.166	.500	.692	*.453*
Recall	.333	.364	.692	*.463*
F1-score	.222	.421	.692	*.445*

Table 11: Performance of our classifier on the test set, trained with only the set of features listed in Table 10. We have listed performance in terms of precision, recall, and F1-score for each of the three classes, as well as average performance.

sized might be because we explicitly left participants relatively free to compensate for behaviours of the robot by repositioning themselves. From the dataset, we derived a large set of features, from which we then attempted to select a suitable set for a classifier. To do so, we tried a range of different feature selection mechanisms with various hyperparameters.

Feature selection proved challenging, but in the end we managed to find significant improvement upon random performance. While automatic feature selection did not perform well in a participant-independent case, we found a small but significant improvement upon random performance for a suitably tuned participant-dependent case.

As we expected that the feature selection had difficulty to reliably identify suitable features, we then further investigated how well the classifier would perform using a set of features that performed particularly well on one of the training folds (see Table 10). Indeed we found that this allowed us to train a classifier that made a more substantial improvement (compared to a random classifier) in the participant-dependent case. These features all use time-windows that can be computed within 1 second after the end of the approach, which suggest that this detection might be quick enough to allow a robot to respond and try improving its behaviour. Together these findings show that, at least in the participant-dependent case, features can be found that provide information about subjectively perceived appropriateness.

This work presents what is effectively an extensive proof of concept and as such we hope it will inspire future work that goes beyond it. Foremost, we expect that there are many ways in which the performance of the classifier and feature selection can be extended upon and improved. The former might be relatively easy, as we chose to use a standard random forest classifier without further tuning. Extending and improving the feature selection might be more challenging, though we hope our first attempts can guide future work in this direction. Since our dataset was relatively small, especially given the amount of features we considered, the collection of a more extensive dataset would be an important next step.

Our findings indicate that our feature selection failed to reliable select suitable features, which suggests that there are opportunities for more sophisticated feature selection. One specific limitation is that, in our chi-squared scores based selection, we computed all scores independently – computing joint scores, combined with for example greedy selection, might improve effectiveness of the feature selection.

The four features we discussed are also but a first selection; given that we had just this one dataset, we could not test if and how well they generalized. They might work participant-independent, or there might be different features that do. While our data collection was designed to be representative of a conversation with a robot, various choices might have influence the non-verbal behaviours of our participants, which would reduce generalizability of our findings – consider, for example, the wire we used to avoid participants approaching the robot, or our manipulation of environment noise.

Lastly, our conclusions are limited to a participant-dependent case due to the way in which we selected our four features. Future work could well try to overcome this limitation. If, on the other hand, aspects of the participant do play a relevant role, there are opportunities for further investigation into the specifics of these aspects.

Overall, we have taken the first steps, showing that a robot *could* detect it got too close, or stayed too far away, during its approach. This provides a stepping stone for thinking about the question that we started this chapter with; what if a robot could detect when you think it got too close to you during its approach?

In this chapter, we look into improvement strategies in more detail. First, we take a closer look at social appropriateness, parametrizing action descriptions to better relate them to the available feedback information. Then, we describe a study in which a telepresence robot uses different improvement strategies to accommodate hearing problems. This experiment, conducted with elderly participants in the context of the Teresa *project (see Chapter 3), showed that our participants significantly appreciated the robot moving closer or turning up its volume over not using any improvement strategy at all. We further saw big individual differences in which of those two improvement strategies our participants preferred. Overall, this suggests that the use of improvement strategies can be beneficial to interactions – and that having multiple improvement strategies to accommodate individual preferences may well be desirable.*

The experiment described in this chapter has previously been published [102].

6 IMPLEMENTING IMPROVEMENT STRATEGIES

> In this story, she is seated in a sturdy yet comfortable chair, her hair pinned up loosely. A big white cat purring in her lap. Somewhat hesitantly a robot approaches her, staying at what it reasons to be a respectable distance. Its volume set to low, so as to not overly disturb her with the news it brings. While the robot is slowly slowing down, it detects the social feedback cues; it suddenly knows it did something wrong in its approach. It knows it did something wrong, but that is not what the robot needs to know right now. What it needs to know is how to make this better, before it is too late...

In abstracto it is simple; after you get feedback, you try to do better. This is also how we sketched improvement strategies when introducing our model of responsiveness (Chapter 4). And, intuitively, it seems easy to come up with strategies for doing better – better your distance if the distance is wrong, better your volume if people cannot hear you, or simply ask for suggestions on how to better one's behaviour.

But how does one know what is 'better' and *what* should be bettered? And, in line with that question, how does one know which of a range of possible alternative actions is a suitable improvement?

The starting point to finding what is 'better' can be the available feedback information. Depending on its **type** (basic, comparable, directional), or mixture of types, it could give more or less explicit information about which other action the agent should try. At the same time, the feedback information can have limited **availability** and/or **reliability**. Even though it is likely that interactees will want their feedback information to be understood, and could adapt it accordingly, in most situations the feedback information will not directly indicate which action an agent should use.

To some extent, what is 'better' is also dependent on what social appropriateness entails for an agent; the different attitudes and needs that play a role, as well as their relative **priorities**. It is worth noting that the **needs** can include both those of the interactee(s) and those of the agent. They can also be more related to the intended function of a robot; for example, a robot that is designed to give people flyers might deliberately choose to approach people who seem like they are not interested [85]. Incorporating these needs in the interaction will require an agent to balance them against each other, negotiating through the interaction their relative importance. The different needs and attitudes can also limit the risk an agent can take in exploring alternative actions, by putting a high cost on making 'mistakes'; this leads to a consideration similar to that between exploration and exploitation [80].

But these partial answers still leave open one key aspect; establishing an explicit relation between the social appropriateness (and the way it is expressed in the available feedback information) and the actions available to an agent. How can we desribe the direction that an agent could try to improve in, capture it in terms of actions?

In this chapter, we will approach this question from two directions. First, we will take a closer look at the structure of social appropriateness and its relation to actions (Section 6.1). Second, we will discuss an experiment in which we investigated different robot response behaviours to accommodate hearing problems (Section 6.2) and two similar studies into compensating for personal space invasion with an apology (Box 7). Our results show that, in this context, improvement is desirable – but not all improvement is equal.

6.1 THE STRUCTURE OF SOCIAL APPROPRIATENESS

It is convenient to think of social appropriateness as if it applies to an action; it was wrong to move as I did, it was right to turn up my volume, etcetera.

This is, ultimately, an untrue simplification; as seen in our formalisation (Chapter 4), the action influences the world state, which in turn includes the relevant attitudes of the interactee(s). Thus, the action can have another effect on the world state than was originally intended. And, beyond that, there are many other factors of the setting that could also influence the attitudes of the interactee directly or indirectly.

Such influences can make it harder to get positive feedback from the interactee(s), but it can also work to the benefit of the agent. For example, the act of making the effort in itself could positively change attitudes (Box 6), or interactees could deliberately make their social feedback cues more clear if they feel an agent does not understand them. Consequently, the available feedback information on the social appropriateness can be a constantly and complexly changing whole.

It is within this context that we are trying to find a way to relate the actions to the available feedback information – for if we cannot, we cannot use the feedback information to inform effective improvement strategies. We will discuss this below, but before we can do so, we will first turn the actions into something that can be related to.

6.1.1 *Parametrizing action descriptions*

Thus far, we have treated actions as elements in a set of possible actions, without any assumed relations between them. As a result, our formalisation can in its current form not describe such relations, nor the relation between actions and their (expected) outcomes.

As we work towards the attitudes, which are part of the setting, we will look for a relation in the way actions relate to the setting. For example, we can describe an action in terms of the (intended) resulting distance, or in terms of the (intended) resulting volume setting.

To this end, we will parametrize our action descriptions. Such parameters could be 'distance to interactee' or 'volume setting', and would each capture one aspect of the (expected) outcome of an action.

6.1.2 *From chaotic to lawful*

With these action parameters we have something in the setting that we can try to relate to feedback information. Yet, we do not yet have a relation between action parameters and the attitudes of the interactee(s). There is a range of possible such relations, that we will try to capture by first discussing their extremes: chaotic, and lawful. Both of these extremes have their own characteristics that, as we will argue, make them less suitable for a responsive approach – it is between these extremes, neutral, that responsiveness thrives.

CHAOTIC The one extreme, **chaotic**, is the case where there is no available relation between the action parameters and the feedback information. As far as the agent can discern, the feedback information is a random function; there is no way to relate it in a meaningful way to the action parameters available. When only basic feedback information is available, it will most of the time result in this kind of chaotic structure.

Given the lack of information to inform an informed decision, the best an agent can do with this type of feedback information is to just keep trying. This is a very limited form of an improvement strategy, and thus a very limited form of responsiveness. One way to try and circumvent this would be to explicitly look for other (less chaotic) kinds of feedback information, e.g. by explicitly asking what the agent should do.

A possible cause for a chaotic relation between the action parameters and the feedback information, is a lack of suitable action parameters. If no suitable action parameters have been found, the feedback information will necessarily have appear chaotic from the perspective of the agent. This implies that responsiveness crucially depends on meaningful action parameters to fully function.

LAWFUL The other extreme, **lawful**, is the case where there is a known relation between the action parameters and the feedback information. In this case, the agent would know that the feedback information can be expressed as a function of known form that depends only on the action parameters.

If this function is fully known, without any free variables, there would be no need for responsiveness. In this context, the main issue becomes detecting all the relevant aspects of the setting reliably, and then using that knowledge with the function to find the best possible action. In other words, in this case, a setting-specific approach would likely be more suitable.

If this function has free variables, then learning the free variables would, in the long run, be a very effective strategy. In this case, the early interactions could be seen as a social calibration, trying to establish the value of those free variables. An example would be to assume that people have a preferred but-unknown volume setting, and then use calibrations to find that volume setting. After such calibrations, the function would thus be fully known for the calibrated case. Thus, in the long run, this case would not really need responsiveness, though it might still be of some help during the calibrations.

At this end of the spectrum, more static (or setting-specific) approaches would thus clearly be very suitable, probably more so than responsiveness.

NEUTRAL Between having no relation available at all (chaotic), or a mostly available relation (lawful), **neutral** is the case where some aspects of the relation are known. In this case, the agent would know that there is some sort of (cor)relation between the action parameters and the feedback information.

On the one hand this would mean that there is no known way in which the relation can be fully expressed in terms of the action parameters (as that would be fully lawful). This could be simply because that way of capturing the relation is not known yet. It could also be because the feedback information depends on more than just the action parameters – such as the mood and personal background of the interactee – in a non-observable way. As we have argued in our formalization, this latter situation is quite likely – and one of the reasons we think responsiveness is valuable.

On the other hand, the relation being neutral means that there *is* a (cor)relation between the feedback information and the available set of action parameters. For example, it could be known that the comparable feedback information correlates with the action parameter of distance to the interactee – even a minimal correlation such as this would already provide information that could help guide improvement strategies.

As stated at the beginning of this section, these different kinds of relations are but three points on a whole spectrum. The actual relation between feedback information and action parameters could be chaotic, neutral, or lawful, but it could also be between chaotic and neutral, or between neutral and lawful. For example, we could have a lawful relation with so many relevant action parameters and free variables, that from a practical point of view it is more effective to approach it as being more neutral. Or we could have a neutral relation with rather unreliable feedback information, effectively making the relation something between chaotic and neutral.

Barring the chaotic extreme, the mere fact that we are trying to find a relation between a function and the actions can well be seen as a form of (machine) learning. As such, it might well benefit from the work in that field. Barring the lawful extreme, it is a specific case of (machine) learning though, where (a) the function could change over time both through and independent of the interaction, and (b) learning the function is not the main purpose of the agent – following our earlier distinction between types of purpose.

6.1.3 *Building a strategy*

In the above, we have established several aspects that together describe the manipulation of the action parameters – the improvement strategies. Specifically, we have parametrized the actions of the agent, ideally resulting in a set of *action parameters* that have a *relation* to the feedback information in a manner between chaotic and lawful.

Before these aspects can be used to create an improvement strategy, there is one last aspect that needs to be considered: the different ways in which actions affect the action parameters. For some action parameters it may be impossible to 'jump' from one value for an action parameter to another, while for others this could be possible. For example, the distance to the interactee is not something that can be changed in a flash, while a volume setting *can* be changed in just a moment.

This means that for some action parameters, going from one value to another will be a transition depending on the **available manipulations**. Such transitions may well yield more feedback information, depending on the availability and reliability of the feedback information. For example, if fine-grained feedback information is available constantly and reliably, a viable strategy for finding the right approach distance during an approach could be to keep getting closer and closer, stopping when the feedback information suggests that the current distance is sufficient.

Together, these aspects can be used to capture, explicitly, how an agent goes from feedback information to selecting actions that help the agent improve. Starting point is the feedback information (with type, availability, and reliability) which is the target of the improvement strategy, the **what** that the agent is trying to change. The purpose (with needs and priorities) tells the agent **why** it wants to change, giving a desired direction for change. And, lastly, since the agent can only manipulate the setting indirectly, through its actions, it is important to consider **how** the feedback information and the actions could be related (with action parameters, their relation with the feedback information, and the available manipulations).

In the next section we will give an exploratory example of filling in these properties, comparing two different action parameters.

6.2 INVESTIGATING IMPROVEMENT STRATEGIES; ROBOT RESPONSE BEHAVIOURS TO ACCOMMODATE HEARING PROBLEMS

The work described in this section has previously been published as; [102].

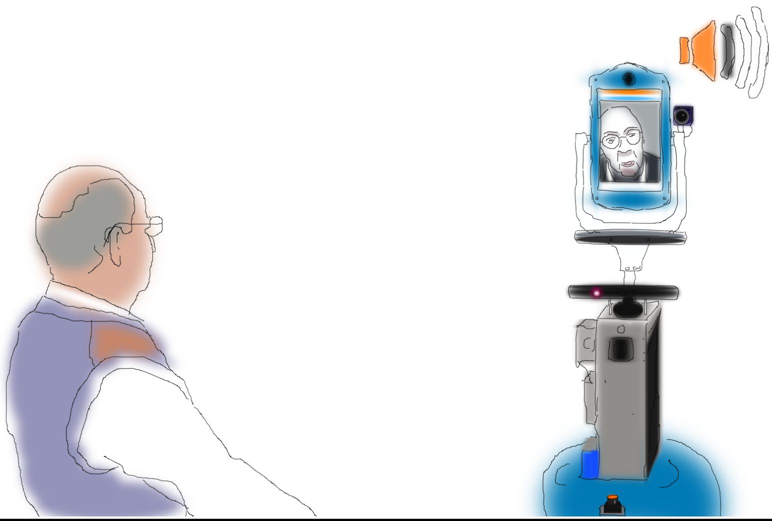
We will in this section look into improvement strategies, using an experiment to compare two different action parameters. The main aim of this section is to investigate if, as we have thus far assumed, people would indeed appreciate a robot to use improvement strategies. For this reason, we have deliberately tried to keep the responsiveness simple and minimal, filling in the properties of the improvement strategy accordingly (see Table 12).

What improvement strategy is appropriate for a social robot will depend on the context in which it is to function. For example, for a robot that helps lifting people out of bed it is necessary to get intimately close, while for a telepresence robot such intimate distances probably are less appropriate. An important aspect of this context are the specific individual needs of the users.

To return to the context of this thesis, we will here again look at elderly, specifically elderly with hearing problems. Hearing problems have a high prevalence among elderly (e.g. [10, 22]). They are frequently, though usually only briefly, mentioned as having a strong influence on the quality of interaction between robots using/supporting conversations and elderly (e.g. [75, 82]). Showing response behaviours to try and resolve hearing problems could thus be a good contribution to any robot that is to communicate through audio with elderly, such as for example (semi-autonomous) telepresence robots.

One way to handle hearing problems is by mimicking the 'leaning' behaviour commonly observed in this user group, where people actively lean in to intimate distances during conversations [102, 105]. Similarly, a social conversation robot could also reciprocate such leaning behaviour by moving closer.

An alternative would be to instead change the volume settings of the robot (used by e.g. [82]). Though in a way less human-like, this could be equally (or more) effective in resolving the hearing problems.



	Property	Value
Feedback information	Type	Simple (sufficient) : Wizard-of-Oz looked for any (verbal or non-verbal) signal that the interaction target had difficulty understanding the visitor
	Availability	Single signal, becoming available after the interaction target has difficulty understanding the visitor
	Reliability	Human-level reliability, given the use of a Wizard-of-Oz
Purpose	Needs	The interaction target and the visitor need to understand each other
	Priorities	Within this experiment, we have looked at exploitation only
Relation	Action parameters	Distance to the interaction target, volume setting
	Relation	Assumed to exist based on literature, subject of the experiment
	Action manipulation	Within this experiment, we had one manipulation for each action parameter only

Table 12: Overview of the properties of improvement strategies, as filled in for the experiment on response behaviours to accommodate hearing problems. The focus of the experiment was on the comparison of behaviours for two action parameters (distance and volume), and we have subsequently tried to keep the rest of the properties as clean and controlled as possible.

"Whoops I'm sorry"

When people attempt to improve their behaviour, especially after making a big social 'mistake', they often don't just try to improve – they also apologize. So, say a robot gets too close to someone, invading their personal space, should apologizing then (also) be part of its improvement strategy?
This question was investigated by one of our Bachelor students, Derk Snijders, in a between-subject study (n=45), where he compared perception of a robot (1) approaching to a normative distance, (2) getting much too close, and (3) getting much too close and apologizing. He found that the apologizing robot was perceived as the most 'sensitive' – even surpassing the robot that did not make a mistake at all.
Another of our Bachelor students, Paulius Knatauskas, looked further into these effects of apologizing, combining it with an attempt to defuse the robot's mistake of getting too close by using humour. He conducted a 2x2 between-subject study in a natural setting (140 interactions initiated), manipulating the use of a joke ("Whoa, are you still alive?") and/or a joke after his robot would approach people to tell them a story about pandas, getting close enough to invade their personal space. His results suggest that in particular the combination of apology and joke is effective, not only on perception of the robot, but also on how willing participants were to fill in the questionnaire when the robot asked them after the interaction.
Together, these findings suggest that a good apology can, indeed, be an effective part of a robot's improvement strategy.

Box 7: Defusing personal space invasions. This work has been conducted by Derk Snijders [87] and Paulius Knautaskas [52] as part of their Bachelor's theses, whom I had the pleasure of supervising in the process.

Which of these two response behaviours would elderly prefer a (semi-autonomous telepresence) robot to show in response to hearing problems? In this section we will report on a small experiment in which we compared these two approaches against the baseline of not responding at all.

6.2.1 *Methods*

To investigate the effect of the different response behaviours, we set up a small experiment as part of a larger evaluation session for the Teresa project. The response of the robot to hearing problems was manipulated as a within-subject variable; in counterbalanced order, all participants saw the response behaviours 'move closer', 'turn up volume', and 'do nothing' (see Figure 12).

In each session one participant (the **Visitor**) sat in a remote location and used the robot in another room to interact with one or two other participants in the same room as the robot (the **Interaction Target(s)**).

6.2.1.1 *Procedure*

The Interaction Target(s) were seated behind a table, with the robot on the other end of it at a distance of approximately 1.5m. To ensure that hearing problems would arise, the volume of the robot had been turned down to a barely audible level. An experimenter explaining the procedure sat with the Interaction Target(s) during the experiment.

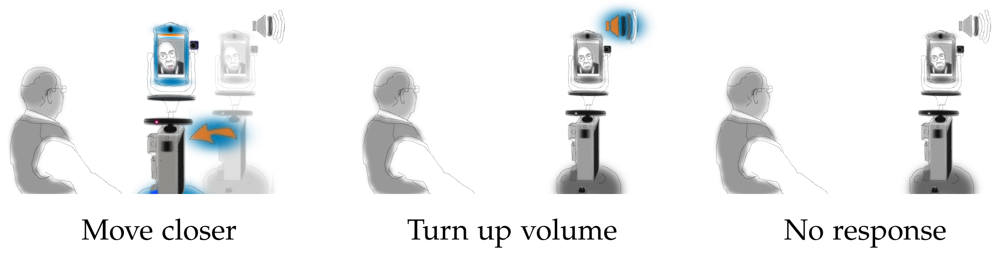


Figure 12: Illustration of the three different response behaviours used in the experiment

To make the conditions more comparable, the experiment started with a full briefing on the aim and the procedure of the experiment. After this, there were three trials in which participants had a brief conversation with each other that was terminated after about two minutes by the experimenter. In each of these trials, as soon as the Interaction Target(s) expressed, verbally or non-verbally, having hearing problems or after approximately one minute, a Wizard of Oz showed one of the three response behaviours in counterbalanced order. For 'no response', no behaviour was shown. For 'move closer', the robot approached the Interaction Target(s) to a distance of around 0.8m. For 'turn up volume', the volume settings were turned up a bit, which was also visible in the interface. To ensure functional comparability, none of these changes was sufficient to completely resolve all hearing problems. At the end of each trial, the robot was returned to its initial position and volume setting. The experiment was concluded with a brief (paper) questionnaire.

6.2.1.2 *Task*

To stay close to the intended use of the robot, the task of our participants was to have a conversation. For this, we asked them to discuss questions of the Proust questionnaire[1], such as, for example, "what do you appreciate the most about your friends?" Specifically, we asked the Interaction Target(s) to read out self-selected questions and the Visitors to discuss what they thought the Interaction Target would answer.

6.2.1.3 *Materials*

We used a Giraff telepresence robot, with a build-in speaker and microphone. The speaker is located in the base, not its 'head', which may have influenced our findings. The robot was co-located with the Interaction Targets, who were seated at a table in the common area of the care facility where we conducted the evaluation. There were some passers-by.

1 http://fr.wikipedia.org/wiki/Questionnaire_de_Proust

Response behaviour	N	Mean	Percentiles				
			MIN	Q25	Q50	Q75	MAX
No response	18	3.000	0	1.5	3	4.25	9
Move closer	17	6.167	0	5	6.5	8	9
Turn up volume	18	8.235	6	7.5	8	9.5	10

Table 13: Descriptive statistics for the ratings given to the three different response behaviours.

The robot was operated through a computer located in another room. From this room, the Visitor communicated with the Interaction Targets using an screen, web cam and a headset with build-in microphone, all connected to the control computer. The Wizard of Oz used another screen and a mouse connected to the same control computer to display the different robot behaviours as discussed above. We used a modified version of the Giraff interface in which the Visitor could only see the video feed, while the Wizard of Oz saw both the video feed and all interface elements required to control the robot.

6.2.1.4 *Measurements*

At the end of the interactions, all participants were given a brief paper questionnaire consisting of eleven items. All items were in French.

Two items asked them to indicate their most and least favourite response behaviour. A third item then asked them to rate all three different response behaviours on a scale of 1-10.

One item asked them to indicate which three qualities of the robot were most influential in their ratings, based on items for warmth and competence [8] (see Table 14 for the qualities). We then also asked them to rate the behaviour of the robot during the rest of the evaluation session, i.e. without hearing problems and in a setting less controlled than that in the experiment. We included as well an open question for comments and suggestions. The last 5 items considered demographics (age, gender, hearing problems, use of hearing aids, relationship with the other participant(s)).

We recorded the interactions on video and using robot-mounted sensors. The interface as seen by the Visitor was recorded using screen capture software.

6.2.1.5 *Participants*

We had 18 French speaking participants (13 female, 4 male, 1 undisclosed), in six pairs and two trios, all with a prior relation (e.g. friends, family). Age of our participants ranged from 60 to 91, with a mean age of 74. Hearing loss was reported by 7 participants. In one pair, a 10-year old grand-child also joined as Interaction Target, but was excluded from analysis.

6.2.2 *Findings*

Summaries of our main findings can be found in Tables 13 and 14. Twelve participants indicated that they preferred the 'turn up volume' behaviour, while the other six instead indicated a preference for 'move closer'. The ratings of these behaviours matched those preferences for 89% of the participants, though many asked for clarification of the rating questions.

Since the rating of the response behaviours was not normally distributed (Shapiro-Wilk, p=.135, p=.039, p=.053) we ran a Friedman test, which found a significant difference in rating ($\chi^2(2)=25.344$, $p<.0005$). We did a post hoc analysis with a Wilcoxon signed-rank test (significance level .017, with Bonferroni correction). The ratings for 'move closer' were significantly higher than those for 'no response' (Z=-2.917, p=.004). The ratings for 'turn up volume' were significantly higher than both those for 'no response' (Z=-3.628, p<.0005) and those for 'move closer' (Z=-2.462, p=.014).

This analysis made the simplifying assumption that the participants can be treated as independent comparable measurements, despite being in the same group and having one of two roles (Visitor/Interaction Target). A series of Pearson's Chi-square test found no significant correlations of either group or role with the ratings, which supports this assumption. The aforementioned significant differences all hold when looking at the Interaction Targets only (N=10), only the difference in rating for 'turn up volume' and 'move closer' is no longer significant (Z=-1.364, p=.172).

6.2.3 *Conclusions and Discussion*

We have compared three different ways in which a semi-autonomous telepresence robot could respond to hearing problems, based on two action parametrizations for that robot. We found high ratings for 'turn up volume', significantly surpassing the ratings for 'move closer'. Both of these were rated significantly higher than 'no response'.

There do seem to be further individual differences, as one third of the participants indicated they prefer the 'move closer' behaviour. We only used general ratings for this, but our participants most commonly indicated to have based their judgement mostly on the qualities 'Intelligent' and 'Helpful'. Since the relation between the action parameters and feedback information is individual in this context, it seems to not be a completely lawful relation – which would make it more suitable for a responsive approach, as argued above.

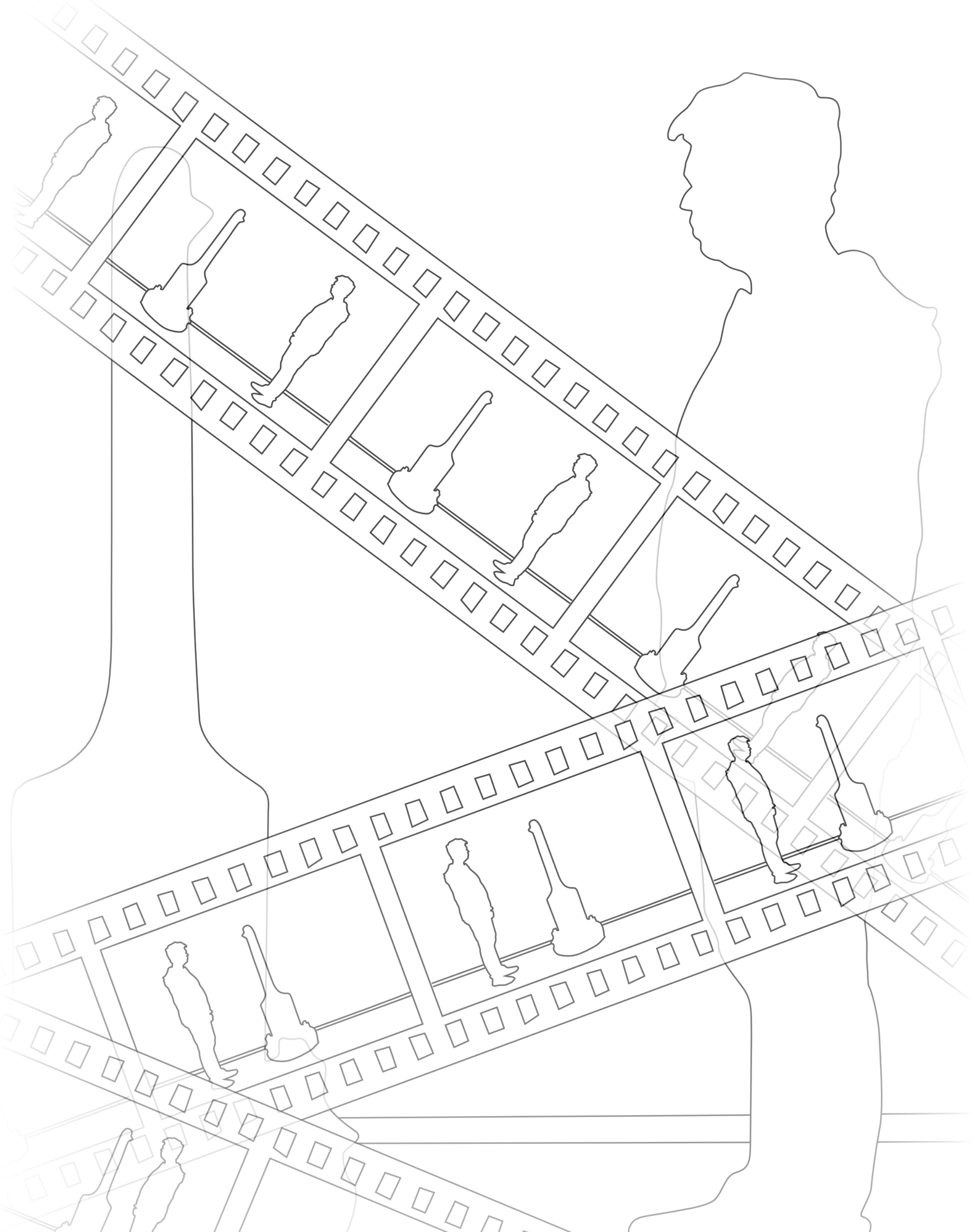
Agréable (Pleasant)	**Sensible** (Sensitive)	**Amical** (Friendly)	**Utile** (Helpful)	**Affable** (Affable)	**Sympathique** (Likeable)	**Accessible** (Approachable)	**Sociable** (Sociable)	**Intelligent** (Intelligent)	**Organisé** (Organized)	**Expert** (Expert)	**Réfléchi** (Thorough)	**Efficace** (Effective)	**Approprié** (Appropriate)	**Attentif** (Attentive)
2	0	2	9	2	1	4	4	10	2	0	4	5	4	5

Table 14: Number of times the different qualities were checked as being most influential in giving the ratings (total = 54).

A few limitations need to be taken into account. Our findings may well be specific to the setting used in the experiment here reported, e.g. 'turn up volume' may be perceived as less appropriate if the noise could disturb others. Also, since we used a Wizard-of-Oz approach, rather than online detection of the social feedback cues, it could still be challenging to implement this kind of behaviour.

Overall, our findings demonstrate that trying to accommodating hearing problems is a desirable feature in this setting. A general approach like turning up the volume when required could work in general cases. If possible, a more personalized solution could be to also/instead move closer if the user would so prefer.

Interpreted more broadly, this shows that, indeed, it is possible to implement effective improvement strategies. In addition the individual differences in preferred action parameter suggest that in the ideal case an agent would have multiple improvement strategies at its disposal, to accommodate.



In this chapter, we investigate how people perceive the relation between approach distance, social feedback cues, and improvement strategy. More specifically, we look at different 'reasons' that could cause people to consider it appropriate if a robot uses the improvement strategy of moving back. We conducted a 2×2×2 online video study manipulating social feedback cues, approach distance, and the use of the improvement strategy of moving back. In line with what a setting-specific approach would predict, initial approach distance was once such 'reason'; we found that participants judged the positioning as less appropriate – and more strongly agreed that the robot should move further back – when the robot used a close rather than a normative initial approach distance. In line with what a responsive approach would predict, we also found another 'reason'; participants judged the positioning as less appropriate when the robot did not move back in the face of a strong social feedback cue. Overall, this suggests that both setting-specific and responsive aspects influence whether or not a robot needs to move back.

7

PERCEPTION OF SOCIAL FEEDBACK CUES AND ADAPTATION

In the previous chapters, we have discussed several factors that could cause social positioning behaviours to be perceived as more or less appropriate. We know that there is feedback information available from the non-verbal cues of people interacting with a robot (Chapter 5). We know that participants appreciated it when a robot tries to use an improvement strategy, at least in the context of a robot moving closer or turning up its volume to counteract hearing problems (Chapter 6). And, of course, we foundextensive literature on the effects of distance, and setting-specific theories such as proxemics on what is an appropriate distance in which setting (Chapter 2).

But how are these different factors related to each other; what do people perceive as an indicator that a robot should try to improve its behaviour? To make this question more specific we will specifically look at the common behaviour of moving back. Do people, as responsiveness would predict, appreciate it when a robot uses the improvement strategy of moving back *in response to* social feedback cues? And how do people appreciate it when a robot would move back after getting inappropriately close? While the previous chapter showed that people appreciate it *that* a robot uses an improvement strategy, in this chapter will look further into the dynamics of *when* people consider it appropriate for a robot to try and improve its behaviour.

One approach, in line with a setting-specific approach, would be to assume there is a normative distance that can be violated. The specifics of that distance would depend on a range of factors, but if it is known, the robot should just aim for that distance. The logical implication would be that if a robot gets 'too close', it should move back – while it explicitly should not if it instead ends up at the normative distance. It also suggests that it would probably be even better if the robot would not violate the normative distance at all.

An alternative approach, in line with responsiveness, would be to assume that the appropriateness of an approach can be observed from the reaction of the person being approached. The presence of social feedback information in that reaction should then indicate if the robot should move back or not. According to the responsive approach, it is *if* a robot gets a social feedback cue after its approach that it should move back. While we have looked at social feedback cues (Chapter 5) and improvement strategies (Chapter 6) in isolation, we have not yet investigated this presupposed relationship between the two.

These two approaches to how the different factors combine, can to some extent coexist; it would be quite possible that both the use of a normative distance *and* being responsive to social feedback cues play a role in the way in which a robot's social positioning behaviour is perceived. But if they do coexist, then how do they weigh up against each other?

In this chapter, we will capture these predictions in research questions with hypotheses (Section 7.1), and investigate these questions through an online between-subject video study (Section 7.2). Our results unveil a combination of dynamics to play a role in the appropriateness of social positioning behaviours (Section 7.3), which has implications for both the responsive and the setting-specific approach to social positioning (Section 7.4).

7.1 RESEARCH QUESTIONS AND HYPOTHESES

As the main aim of this chapter is to look into *when* people perceive it to be appropriate for a robot to try and improve its behaviour, our research questions will reflect that. Since we have given two not mutually exclusive accounts for this '*when*', from a setting-specific approach and from responsiveness, we will capture these in the first two research questions. In addition, since there is to our knowledge no prior work on what would happen on the overlap between these two accounts, we also include a third, exploratory, research question on that. As the goal is explicitly to quantitatively test and compare different '*when*'s, these research questions are all focused on perception from a third-person perspective – which also aligns with our use of a video study to investigate these questions.

To make 'appropriateness' more specific and measurable in this context, we will distinguish two specific aspects based on our work in the previous chapters. First, we will look at how the eventual positioning of the robot is perceived. Following our work in Chapter 5, we will not only look at perceived 'appropriateness' of that behaviour, but also investigate if participants think the robot should move closer and/or further away. Second, building on the measures used in Chapter 6, we will look at how the robot itself is perceived by investigating to what extent participants consider it as warm, competent, and discomfortable.

This leads to the following three research questions;

Research question 1 What are the effects of initial approach distance (normative/too close) and the robot subsequently moving back (moving back/-not) on perception of the eventual positioning as appropriate, too close, and too far away? And on perception of the robot as warm, competent and discomfortable?

Research question 2 What are the effects of a social feedback cue (strong, minimal) indicating a robot is too close for comfort and the robot moving back (moving back/not) on perception of the eventual positioning as appropriate, too close, and too far away? And on perception of the robot as warm, competent and discomfortable?

Research question 3 How do the different effects of approach distance, given social feedback cue, and the robot moving back weigh up against each other?

Based on a setting-specific account of social positioning, we would expect that an important factor will be if the robot ends up at a normative distance. That is, we expect that it will be judged as less appropriate when the robot ends up closer (too close and then not moving back) or further away (normative and then moving back) than the normative distance. We further hypothesize that participants will suggest changes to the behaviour of the robot (moving closer/going further away) reflecting this norm, and that perception of warmth and competence will follow these same trends, while perception of discomfort will follow an opposite trend.

Based on our theory of responsiveness, we first and foremost hypothesize that if a feedback cue is given, moving back will be perceived as more appropriate, and result in a more positive perception of the robot, than not moving back. As a stronger form of this hypothesis, we would expect that moving back will be perceived as more appropriate than not moving back when a feedback cue is given, and not moving back is perceived as more appropriate than moving back when there is no strong feedback cue indicating the robot is too close. Again, we would expect perception of the robot as warm and competent to follow this same trend, with perception of the robot as discomfortable going against it. Furthermore, and in line with this, we would expect people to more strongly think the robot should get further away if a feedback cue was given without the robot moving back, and vice versa, that the robot should get closer if the robot moved back without a feedback cue.

While we have used the setting-specific approach and the responsive approach to make predictions, there is – to our knowledge – no prior work on what happens in their overlap. It is intuitive to expect, as both approaches predict, that if a robot gets too close and gets a strong feedback cue, that it would be more appropriate for it to move back. But what happens if a robot uses a normative distance, gets a strong feedback cue, and then does not move back? Will the normative distance take prevalence, or will participants judge the behaviour as less appropriate for not responding to the feedback cue? As we have no specific grounds for any hypotheses, we will treat the third research question as more exploratory.

7.2 METHODS

We conducted a 2x2x2 between-subject video-based online experiment. Each participant saw a video in which the robot approached a person (the **interactee**), edited to ensure comparability (Section 7.2.2). The use of videos allowed for a clean and independent manipulation of approach distance (validated through a pre-study), strength of the given social feedback cue, and of whether the robot moved back or not (Section 7.2.1). In line with the constructs defined in our research questions, after watching one of the videos, participants were asked: (1) to what extent at the end of the video, the robot was positioned appropriately and/or should get closer or go further away, (2) to what extent they perceived the robot as being warm, competent and/or discomfortable (Section 7.2.3). Participants were recruited through an online platform (Section 7.2.4).

7.2.1 *Manipulations*

As described above, we manipulated initial approach distance, moving back of the robot, and the strength of the social feedback cue. Each of these manipulations was achieved through independent manipulation of the created video material (discussed in more detail below), ensuring that the manipulations were independent. We will here give a more extensive overview of how we created and validated these different manipulations. A comprehensive overview of all manipulations can be found in Table 15.

7.2.1.1 *Initial approach distance*

To find which initial approach distance would be considered as normative by people watching the videos, we first conducted a 12×1 within-subject pre-study, investigating the effect of twelve different approach distances on perception of the positioning of the robot as appropriate. A complete overview of the questions asked, and the outcomes, can be found in Figure 13. We used the same measures that we also used in the final study (Section 7.2.3), except for those measuring perception of the robot and the manipulation checks. The videos were created to cover a range of approach distances using the same procedure as used for the final videos, with a minimal feedback cue from the interactee, but ended immediately after the initial approach. Participants saw each of the twelve videos in random order, with a still of the end position being shown while the video did not play, and answered the accompanying questions. A total of 45 convenience-sampled participants started the questionnaire, with 37 completing it. They had a mean age of 33 (ranging from 19-77), were mostly born in the Netherlands (76%), and had a fair distribution of gender (19 identified as female, 18 as male).

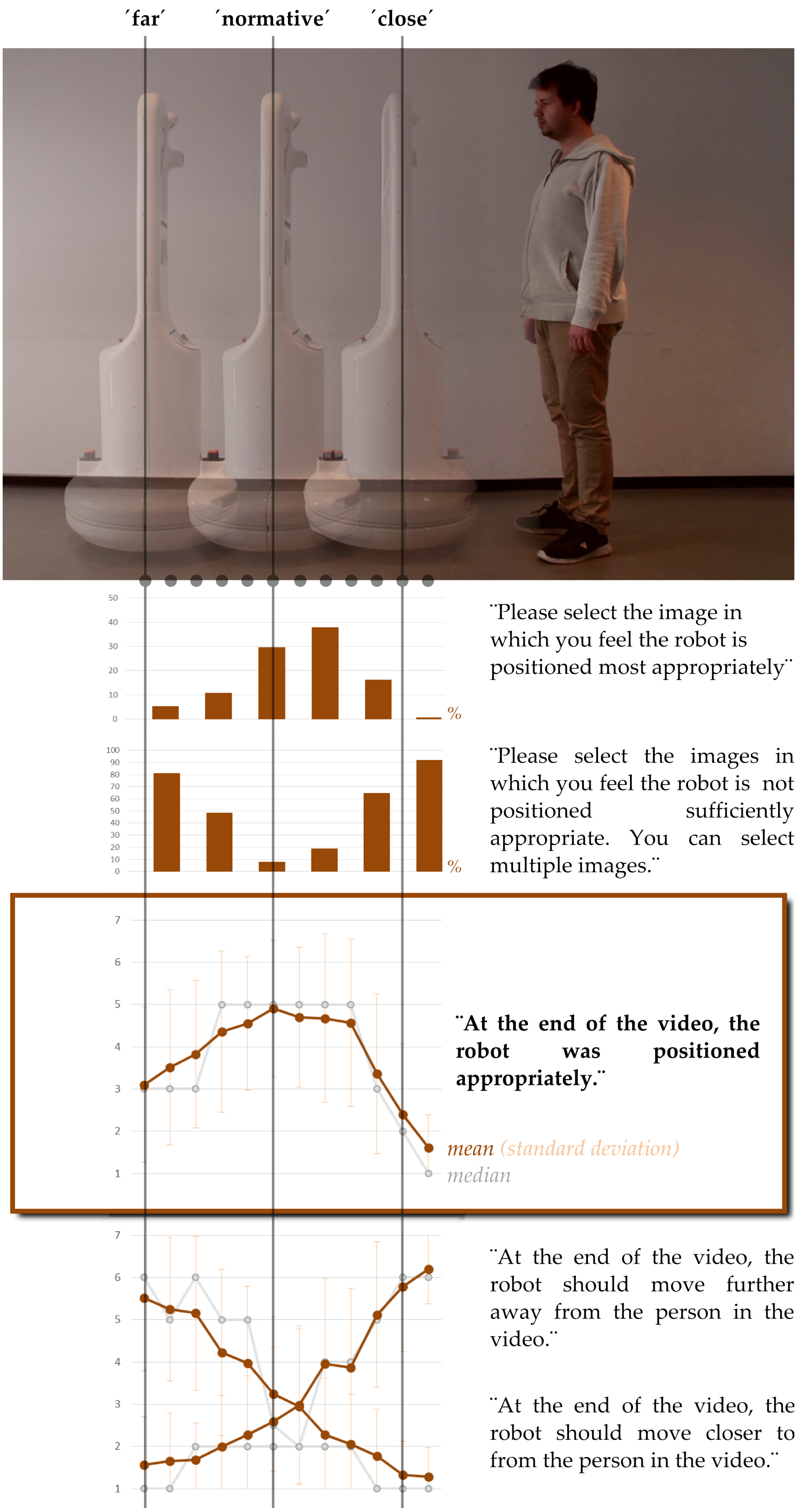


Figure 13: Overview of the participants' judgement of the twelve different approach distances investigated in the pre-study. The three vertical lines indicate the three distances we selected for use in the study; 'far', 'normative', and 'close'. Though we here illustrated those three distances on a still, participants saw the robot in motion.

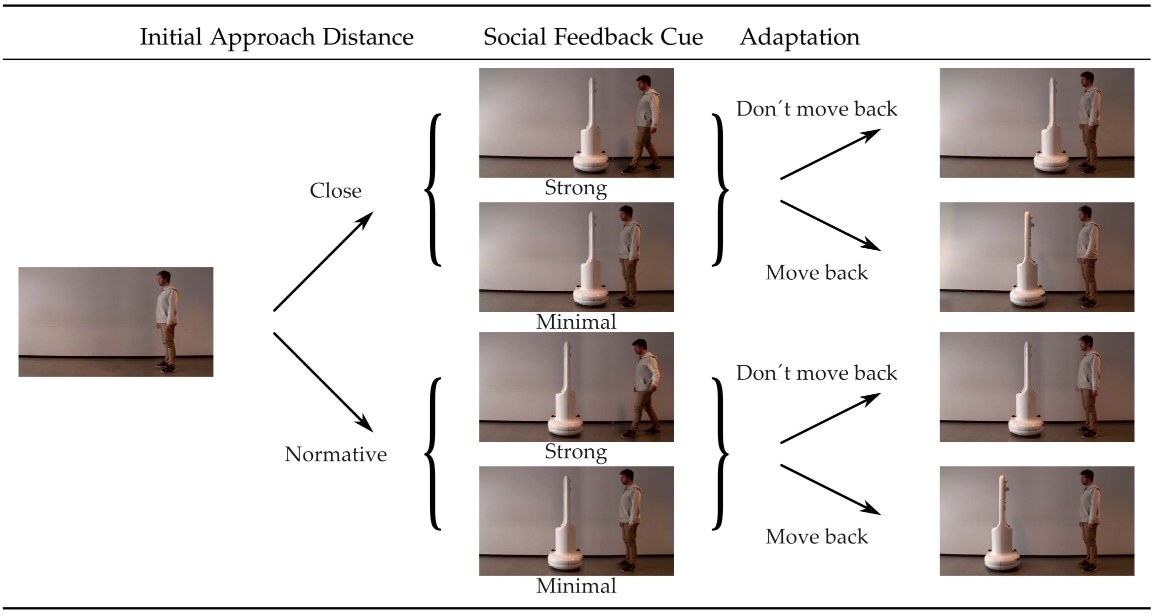


Table 15: Schematic overview of the manipulations. All videos started showing just the interactee, after which the robot approached using either a close or a normative initial approach distance. In parallel to the end of the approach, the interactee would give either a strong or a minimal social feedback cue. Then the robot would either move back or not, ending in one of three distances; 'close', 'normative', or 'far'.

We found a significant effect of approach distance on participants judging the position of the robot at the end of the video as appropriate (Friedman test, X2(11) = 128.685, $p<.0005$). Post-hoc analysis revealed that specifically the differences between the medium approach distances and the more extreme approach distances (relatively close, relatively far) were judged significantly different. Based on this, we chose the 'close', 'far', and 'normative' distance to be used – with significant differences between 'close' and 'normative' ($p<.0005$) and between 'normative' and 'far' ($p<.0005$).

The 'normative' distance thus chosen (approximately 95cm) also aligned with the distance chosen by the interactee in a stop task. The distances also seem to be much in line with the normative distances for not close personal interaction that can be found in the work on proxemics [31].

7.2.1.2 *Strength of social feedback cue*

What is a suitable social feedback cue in this context? To avoid making unnecessary assumptions, we chose to use naturally elicited strong/minimal feedback cues.

We took two shots of our interactee; one where the robot used an approach distance that the interactee considered as comfortable, and one where the robot came much closer. Indeed, we saw that this resulted in two starkly different feedback cues, where in the latter the interactee gave a strong reaction by physically stepping back, while in the former he would only sway his upper body a little bit. These reactions also align with the features found to contain feedback information in Chapter 5.

7.2.1.3 *Adaptation: Moving back*

In our manipulation of moving back, the robot would either move back or not. Since we had established a normative distance, the moving back behaviour was created such that with a close initial approach distance, moving back would result with the robot at a normative distance. When the initial approach distance was normative, moving back in the same way instead resulted in the robot ending up at a 'far' distance (see Table 15).

7.2.2 *Videos*

Since the study explicitly considers the social feedback cues given by the interactee, the videos needed to be shot in third person. We created a clean lab setting such that the robot and interactee could both easily be seen from the side. The background was a nondescript plain white wall. We lit the wall to reduce the shadows of the robot and the interactee visible on the wall.

The robot used in the video was the robot developed in the aforementioned TERESA project. This human-sized, mobile, white robot has no visible wheels.

Men are, in general, found to use/prefer bigger interaction distances than women [2], and as this would allow us to create stronger differences between how the different approach distances would be perceived as more or less socially normative, we subsequently used a man as our interactee. We first established what the interactee subjectively perceived as a pleasant interaction distance through a simple stop task; we would approach with the robot and then stop when the interactee indicated so. We also tested and confirmed that the interactee perceived it as uncomfortable when the robot came much closer than that.

We recorded a total of two shots (in multiple takes). In both shots, we let the interactee free to respond as he saw fit, with one exception; to avoid influences of the response behaviours on the approach distance, the interactee was instructed to put and keep his left foot on a marker on the floor. The first shot was of the robot approaching the interactee, using the interaction distance preferred by the interactee. In this shot, the interactee did not move his body much throughout the interaction; only swaying his body back and forth a little bit as the robot came to a stop. The second shot was of the robot approaching the interactee, but getting much closer than what the interactee had indicated to prefer, moving back to the preferred interaction distance after the end of the approach[1]. In this shot, we saw a lot of movement in response to the end of the robot's approach; in most takes, the interactee would actively step back as far as he could with his right foot. When the robot moved back to the preferred interaction distance, so too would the interactee then put his right foot back next to his left foot.

We then cut and edited these two shots together in a variety of ways to create our different manipulations cleanly and to ensure we manipulated them independent of each other. To get the strong and minimal feedback cues, we used video editing software to remove the robot from the frames, leaving us with just the reaction of the interactee in the two shots. We used one single take of the robot approaching and then moving back (from the second shot), removed the participant from those frames, and then manipulated this take to get all the different robot approach behaviours. For the condition where the robot would not move back, we edited out that bit. To manipulate the approach and retreat distance of the robot relative to the interactee, we shifted the position of all frames of the robot to the left/right as required. In a small pilot we confirmed that our editing was not visible to observers unless explicitly pointed out.

7.2.3 *Questionnaire and procedure*

The experiment was fully presented as an online questionnaire, consisting of several separate pages with a total of 32 questions.

First and foremost we were interested in perception of the eventual positioning as appropriate, too close, and too far away. Following previous work on social positioning, we assessed this perceived 'appropriateness' by asking participants to assess on a 7-point Likert scale (strongly disagree (1) – strongly agree (7)) to what extent they agreed with the statement "At the end of the video, the robot was positioned appropriately." We used similar questions to assess if participants thought the robot should move further away from and/or get closer to the interactee.

These questions were presented on the first page of our questionnaire (after consent and an overview of the questionnaire), which was also where participants were asked to watch the video of the robot approach. This ensured that participants could watch the video as often as they needed while answering these questions. We introduced the context by stating that the aim of the robot was to have a pleasant conversation with the person in the video. The other questions were presented on the following pages, in the order they are listed below. To ensure that participants would not try to look for a 'right' answer, but would really give us their impression, participants could not go back to watch the video again while on those pages.

1 The interactee had consented to this beforehand.

To check our manipulations, we included three manipulation checks. Specifically, we asked to what extent (7-point Likert scale) participants agreed with the statements; (1) that the robot got too close to the interactee at some point in its approach, (2) that the interactee seemed uncomfortable with the approach at some point, and (3) that the robot moved away from the interactee at some point. While these questions are to some extent subjective, they can be related to, respectively, our manipulations of initial approach distance, strength of the social feedback cue, and moving back.

In addition, we were interested in perception of the robot as warm, competent and discomfortable. For this we used the RoSAS [19], which contains 6 items for each of these constructs, that participants were asked to rate as being associated with the robot they saw in the video on a 9-point Likert scale. This resulted in a total of 18 items, which were presented in randomised order. To allow for diligence checks, one item ('responsive') was included a second time as a 19th item.

We further wanted to check that participants in our sample were comparable to those in our pre-study, in terms of their opinion on what would be an (in)appropriate interaction distance for a robot. We thus also included the two questions from the pre-study where participants had to select from six stills with the robot at different distances the one they considered most appropriate (one choice only) and the ones they considered not sufficiently appropriate (multiple choices possible).

We concluded, on the last pages, with demographic questions on age group, gender, education level (tailored to our participants being from the US), and experience with robots. At the end of the questionnaire we thanked the participants, and handled the data for their payment.

7.2.4 *Participants*

Participants were recruited online, using the Amazon Mechanical Turk platform. They received a small compensation for their efforts ($0.70), and took on average between 4 and 5 minutes to complete.

A total of 244 participants filled in the whole questionnaire. Given the nature of the platform used for data collection, we checked all answers before using them. We used a combination of indicators to try and detect lack of diligence, flagging participants if they failed more than two; (1) logically inconsistent answers (e.g. suggesting the robot should both get closer and move further away); (2) wrongly answering our manipulation checks, particularly the one that factually asked if the robot moved back, as that suggested they did not watch the video; (3) giving inconsistent answers to the one item (Responsiveness) that we had included twice in the RoSAS, we also eliminated the one participant who ranked every single item on the RoSAS the same; and (4) being infeasibly quick in answering the questionnaire (several participants took less than 120 seconds to answer the whole questionnaire, with its 32 items)

This resulted in 40 participants being flagged. We checked these 40, and found strong indicators for lacking diligence in 17 of them. These participants were eliminated from the sample, leaving us with 227 participants, of whom we were reasonably sure they had diligently answered the questionnaire.

Given the known effects of culture on social positioning preferences [31, 43], we deliberately limited our participants to be from the US only. Due to a technical error, we did not collect demographic information for 8 of our participants, the demographics reported below are from the other participants. The majority of our participants was around 25-44 years old (25-34, 36.1% and 35-44, 30.8%). Only three (1.3%) were 18-24 years old, the rest was older than 45 (45-75, 31.8%). Gender was fairly evenly balanced between participants, with 41% identifying a female, 54.6% as male, and 2 participants who did not identify with either gender. Of our participants, 54.3% had graduated from college, with 7 participants (9.3%) also having completed graduate school. All but one participant had graduated from high school.

About one third of our participants (31.7%) had no prior experience with robots. Over half (59.5%) had seen robots, 19.4% had interacted with them, 2.2% owned a robot, 1.8% had programmed a robot. Those 44 participants that had interacted with robots did mostly not do so frequently (56.8%), though some did do so once per month (18.2%), once per week (11.4%), or even several times per week (9.1%), up to daily (4.5%).

7.3 RESULTS

After collecting our data and removing the participants who failed our diligence check as described above, we conducted our statistical tests. We first completed our manipulation checks (7.3.1), and then tested for perception of the robot's eventual position (7.3.2) and the robot itself (7.3.3).

7.3.1 *Manipulation checks*

Our manipulation of approach distance was noticed by our participants, as they more strongly indicated that 'the robot came too close at some point' in the close condition (mean rank = 143.67) than in the normative condition (mean rank = 75.29)(Mann-Whitney U test, $U=2571.5$, $z=-7.994$, $p<.0005$, visual inspection showed distributions to be dissimilar). We also confirmed, by visual comparison of bar plots, that the participants in our sample and the participants in our pre-study had similar opinions on what would be an (in)appropriate interaction distance (see Figure 14).

Our manipulation of feedback cue was noticed by our participants, as they more strongly indicated that 'the person in the video was uncomfortable with the approach of the robot at some point' in the strong cue condition (mean rank = 154.08) than in the minimal cue condition (mean rank = 71.21)(Mann-Whitney U test, U=1805, z=-10.084, p<.0005, visual inspection showed distributions to be dissimilar).

Our manipulation of the robot moving back was noticed by our participants, as they more strongly indicated that 'the robot moved away from the person in the video at some point' in the moving back condition (mean rank = 167.10) than in the no moving back condition (mean rank = 57.64)(Mann-Whitney U test, U=288, z=-13.319, p<.0005, visual inspection showed distributions to be dissimilar).

While doing our manipulation checks, we observed more patterns in the answers of our participants. To our interest, it seemed that participants also indicated more strongly that 'the robot came too close at some point' when the robot did not move back (mean 4.444 $\pm$.162) than when it did move back (mean 5.352 $\pm$.153). Similarly, participants also seemed to indicate more strongly that the robot came too close when the interactee gave a strong feedback cue (mean 5.351 $\pm$.152) than when the feedback cue was minimal (mean 4.445 $\pm$.163). We wish to emphasize that these are observations, not conclusions. We also wish to note that these differences are less stark than those between the answers for the robot getting close (mean 6.079 $\pm$.145) and for the robot using a normative initial approach distance (mean 3.717 $\pm$.170).

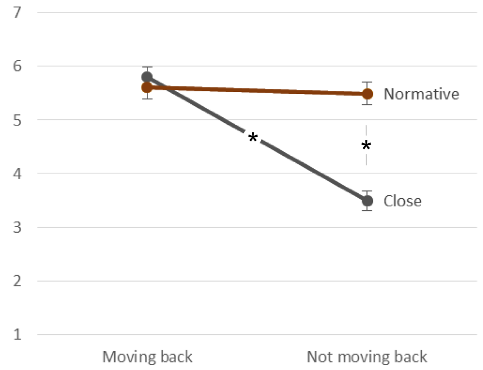
7.3.2 *Perception of the robot's eventual position*

Perception of the robot's eventual position was measured by asking participants to agree with statements that the robot was positioned 'appropriately', should 'move further away', and should 'move closer'. An graphical overview of the findings reported here can be found in Table 16.

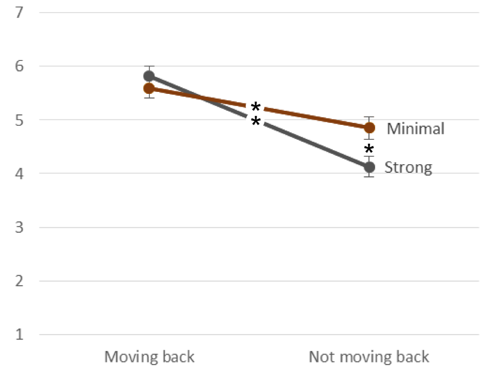
7.3.2.1 *Assumptions*

Before conducting our tests, we first tested the data for outliers, being normally distributed, and homogeneity of variances. There was one outlier on the question on 'appropriateness', but as the data of this participant otherwise did not seem to be irregular, we kept this outlier in our analysis. Data was not normally distributed for any of the questions; visual inspection of the histograms showed that participants mostly used the extreme ends of the scale. The assumption of homogeneity of variances was violated for the questions on 'appropri-

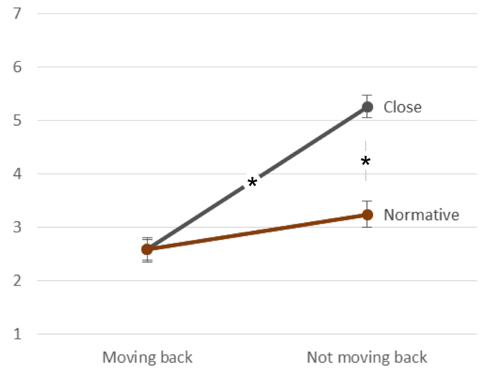
"At the end of the video, the robot was positioned **appropriately**"
Approach distance × Moving back



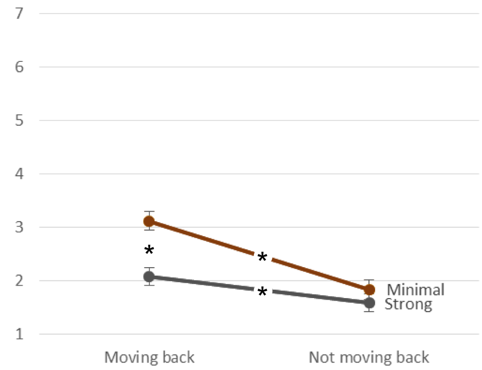
"At the end of the video, the robot was positioned **appropriately**"
Feedback cue × Moving back



"At the end of the video, the robot should **move further away** from the person in the video"
Approach distance × Moving back



"At the end of the video, the robot should **move closer** to the person in the video"
Feedback cue × Moving back



	'appropriately'			'appropriately'			'move further away'			'move closer'		
	close approach		normative approach	strong feedback cue		minimal feedback cue	close approach		normative approach	strong feedback cue		minimal feedback cue
Moving back	5.814 ±0.172		5.605 ±0.203	5.823 ±0.188		5.596 ±0.190	2.586 ±0.197		2.585 ±0.235	2.077 ±0.168	*	3.124 ±0.170
	*			*		*	*			*		*
Not moving back	3.493 ±0.185	*	5.498 ±0.213	4.129 ±0.187	*	4.852 ±0.211	5.265 ±0.212	*	3.245 ±0.244	1.587 ±0.167		1.841 ±0.188

Table 16: Overview of the means and standard deviations for those variables where we found a significant two-way interaction, both in a table and in plots. The '*' in between means denotes significant simple main effects between those means. All questions were asked on a 7-point Likert scale, from 'strongly disagree' (1) to 'strongly agree' (7).

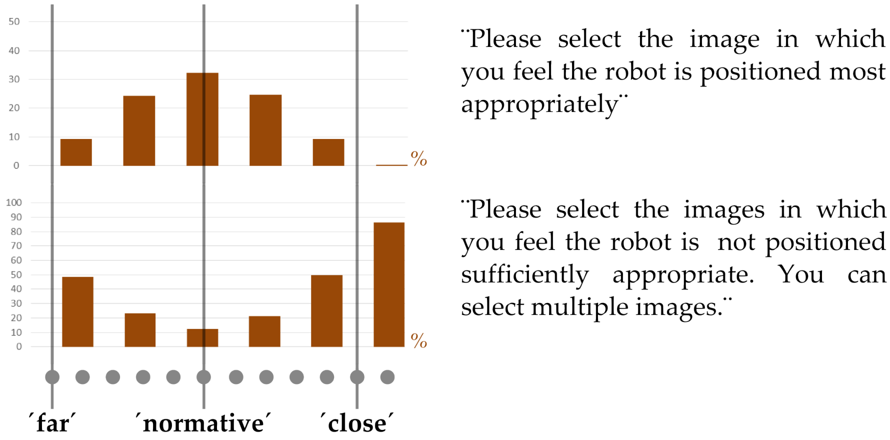


Figure 14: Bar plots for the relative frequency with which participants chose, out of 6 stills with different approach distances, the most appropriate (top plot) and those they did not consider sufficiently appropriate (bottom plot). The x-axes align with the video as in Figure 13.

ateness' and 'move closer', but not for the question on 'move further' (Levene's test for equality of variances, p=.047, p<.0005, p=.311, respectively) – group sample sizes were approximately equal.

Based on this, we chose to use an ANOVA to analyse our data.

7.3.2.2 *Three-way interactions*

We first conducted a three-way ANOVA to control for three-way effects of our manipulations on the questions, but found no significant effect. Not on perception of the robot as being positioned appropriately (F(1,219)=1.646, p=.201), not on judgement that the robot should get further away from the interactee (F(1,219) = .371, p=.543), and neither on judgement that the robot should move closer to the interactee (F(1,219) = .542, p=.462).

Since there were no three-way effects to take into account, we conducted a series of two-way ANOVAs to test our hypotheses.

7.3.2.3 *Two-way interactions for 'appropriate'*

When looking into the two-way interactions for perception of the robot as being positioned appropriately, we found a significant two-way interaction (F(1,219)=32.221, p<.0005) of approach distance and moving back. The simple main effect of moving back was significant when the approach distance was close (F(1,219)=84.713, p<.0005), but not when the approach distance was normative (F(1,219)=.155, p=.694). The simple main effect of approach distance was significant when the robot did not move back (F(1,219)=50.210, p<.0005), but not when the robot did move back (F(1,219)=.612, p=.435).

For the same question, we also found a significant two-way interaction ($F(1,219)=5{,}962$, $p=.015$) of feedback cue and moving back. The simple main effect of feedback cue was significant when the robot did not move back ($F(1,219)= 6.573$, $p=.011$), but not when the robot did move back ($F(1,219)=.716$, $p=.398$). The simple main effect of moving back was significant when a strong feedback cue was given ($F(1,219)=40.779$, $p<.0005$), and also when a minimal feedback cue was given ($F(1,219)=6.880$, $p=.009$).

The two-way interaction between approach distance and feedback was not significant ($F(1,219)=1.455$, $p=.229$).

7.3.2.4 *Two-way interactions for 'move further away'*

When looking into the two-way interactions for judgement that the robot should move further away, the two-way interaction between approach distance and moving back was found to be significant ($F1,219) = 20.529$, $p<.0005$). The simple main effect of approach distance was significant if the robot did not move back ($F1,219) = 39.079$, $p<.0005$), but not if the robot did move back ($F1,219) = .000$, $p=.998$). The simple main effect of moving back was significant if the robot got close ($F1,219) = 85.713$, $p<.0005$), but not (or marginally) significant if the robot approached to a normative distance ($F1,219) = 3.788$, $p=.053$).

We found no significant difference for the other two two-way interactions, between approach distance and feedback cue ($F1,219) = 2.358$, $p=.126$) and between feedback cue and moving back ($F1,219) = .025$, $p=.873$).

7.3.2.5 *Two-way interactions for 'move closer'*

When looking into the two-way interactions for judgement that the robot should move closer, we found that the two-way interaction between feedback cue and moving back was significant ($F(1,219) = 5.227$, $p=.023$). The simple main effect of the strength of the feedback cue was significant if the robot moved back ($F(1,219) = 19.208$, $p<.0005$), but not if the robot did not move back ($F(1,219) =1.019$, $p=.314$). The simple main effect of moving back was significant if the robot received a minimal cue ($F(1,219) = 25.629$, $p<.0005$), and also if the robot received no cue ($F(1,219) = 4.289$, $p=.040$).

We found no significant difference for the other two two-way interactions, between approach distance and feedback cue ($F1,219) = 1.037$, $p=.310$) and between approach distance and moving back ($F1,219) = 1.871$, $p=.173$).

7.3.3 *Perception of the robot in terms of warmth, competence, and discomfort*

We measured the perception of the robot as warm, competent, and discomfortable with the items from the RoSAS [19]. As the scenario and robot were quite different from those used in the paper introducing the questionnaire, we checked if the items still loaded onto the same constructs. To do so, we ran a principal component analysis (PCA) on the 18 items from the RoSAS.

Based on prior tests we concluded that a PCA was suitable, as all items had at least one correlation above r = 0.5, the data had adequacy of sampling (Overall KMO of .882, with KMO's for individual items ranging between .933 and .782), and was likely factorizable (Bartlett's test of sphericity, p<.0005).

PCA revealed three components that had eigenvalues greater than one, together explaining 63.6% of variance (32.9, 20.5, and 10.2% of variance respectively). These three components were mostly consistent with those of the original RoSAS – Warmth, Competence, and Discomfort – only the item 'social' was grouped with the items on Competency rather than those on Warmth. We used the component-based averaged scores for these components.

7.3.3.1 *Assumptions*

Before conducting our tests, we tested the scores for these constructs for outliers, being normally distributed, and homogeneity of variances. There were no outliers. Data was not fully normally distributed for any of the questions; visual inspection of the histograms showed that participants mostly used the extreme ends of the scale, particularly the low end for Warmth and Discomfort. The assumption of homogeneity of variances was violated for Warmth, but not for Competence and Discomfort (Levene's test for equality of variances, p=.001, p=.182, p=.517, respectively) – group sample sizes were approximately equal.

Based on this, we chose to use an ANOVA to analyse our data.

7.3.3.2 *Interaction effects*

We found no significant three-way interaction of our manipulations on Warmth (F(1,219) = .193, p=.661), Competence (F(1,219) = 1.096, p=.296), or Discomfort (F(1,219) = .847, p=.358).

We subsequently looked at the two-way interactions for Warmth, Competence, and Discomfort. We found no significant two-way interactions for Warmth, not between approach distance and feedback cue (F(1,219) = 1.180, p=.279), not between approach distance and moving back (F(1,219) = .640, p=.425), and not between feedback cue and moving back (F(1,219) = .305, p=.581). We also found no significant two-way interactions for Competence, not between approach distance and feedback cue ($F(1,219) = .720$, $p=.397$), not between approach distance and moving back ($F(1,219) = .103$, $p=.749$), and not between feedback cue and moving back ($F(1,219) =.026$, $p=.871$). Neither did we find any of the two-way interactions for Discomfort to be significant, not between approach distance and feedback cue ($F(1,219) = 2.030$, $p=.156$), not between approach distance and moving back ($F(1,219) = .557$, $p=.456$), and not between feedback cue and moving back ($F(1,219) = .294$, $p=.588$).

Since there were no interaction effects to take into account, we thus looked at the main effects instead.

7.3.3.3 *Main effects*

We saw a significant effect of approach distance on all three scores; for Warmth ($F(1,219) = 3.913$, $p=.049$), for Competence ($F(1,219) = 6.804$, $p=.010$), and for Discomfort ($F(1,219) = 13.527$, $p<.0005$).

We also found a significant effect of moving back, but only on the score for Competence ($F(1,219) = 9.891$, $p=.002$). There was no significant effect on Warmth ($F(1,219) = 1.670$, $p=.198$) or Discomfort ($F(1,219) = .132$, $p=.727$).

We found no significant effects of the social feedback cue on either Warmth ($F(1,219) = 1.617$, $p=.205$), Competence ($F(1,219) = .559$, $p=.456$), or Discomfort ($F(1,219) = 2.868$, $p=.092$).

7.4 CONCLUSIONS AND DISCUSSION

In this chapter we have investigated the effects of different factors on the appropriateness of a robot's approach. Specifically, we have looked at the single and joint effects of initial approach distance [close/normative], strength of the feedback cue given in response to that initial approach [strong/minimal], and whether or not the robot used an improvement strategy after the initial approach [moving back/not moving back]. We created videos for each combination of these manipulations, which we used to conduct a 2x2x2 between-subject study through an online questionnaire.

We looked into both perception of the eventual positioning and perception of the robot as warm, competent, and discomfortable. Effects on perception of the robot as warm, competent, and discomfortable were minimal, revealing no significant interaction effects. We did observe, post-hoc, an effect of approach distance on all the constructs, and of the robot moving back on it being perceived as competent. However, given the lack of significant interaction effects, we will focus our further conclusions and discussion here on the perception of the eventual positioning (see Table 16 for an overview).

Our hypothesis for the first research question was based on a setting-specific account of social positioning, and presupposed an interaction

"I'll fix this as quick as I can."

In our video study (Chapter 7), we validated the used approach distances, and used naturally elicited social feedback cues – but we did not really check the used improvement strategy. This leaves open the question if our used improvement strategy also had an effect. To focus this on two aspects, did our choice of the robot's speed and timing when moving back have an effect on perception of the participants in our video study?

One of our students, Reinier de Ridder, investigated this in a small exploratory study (n=31, between-subject). Using the same raw videos as we used in our video study, specifically the one where the robot came close *and* got a feedback cue, he manipulated the speed of the robot moving back [as recorded/quickened] and the timing [immediate/as recorded]. He also included a control condition where the robot did not move back at all.

While the sample size was very small (approximately 6 participants per condition), various interesting patterns emerged. Most notably, it seemed that perceived appropriateness and competence were influenced mostly by the robot moving back or not, while speed and timing seemed to have more of an effect on perceived warmth and discomfort. While further research is needed, this does suggest an intriguing addition to the results presented in Chapter 7: perhaps it is through the aspects of timing and speed that a robot can express personality in these contexts?

Box 8: Exploring effects of speed and timing on perception of the improvement strategy of moving back. This work has been conducted by Reinier de Ridder as part of a small project, whom I had the pleasure of supervising in the process [78].

effect of initial approach distance and moving back. In line with our expectations we found an interaction effect, where participants judged the positioning as less appropriate – and more strongly agreed that the robot should move further back – when the robot ended up at a close distance, when compared to ending up at a normative distance. We further hypothesized that participants would also judge it as less appropriate when the robot ended up at a far distance, but this hypothesis was not confirmed. We also did not see participants agreeing more strongly that the robot should move closer in these cases. In contrast to this, we saw that participants, when judging stills, still frequently judged the 'far' distance as inappropriate (for almost 50% of participants, see Figure 14) – suggesting that the participants did not judge the far eventual distance as appropriate because it was far in itself, but rather because the robot moved back to get there.

Our hypothesis for the second research question was based on a responsive account of social positioning, and presupposed an interaction effect of strength of the social feedback cue and moving back. In line with our expectations we found an interaction effect, where participants judged the positioning as less appropriate when the robot did not move back if the social feedback cue was strong rather than minimal. We further saw that for both a strong and minimal feedback cue, participants judged the positioning as more appropriate when the robot moved back – though participants also agreed more that the robot should move closer in those cases. We further hypothesized that participants would also judge it as less appropriate when the robot moved back without a cue, and while this hypothesis was not confirmed, we did find that participants most strongly agreed that the robot should move closer if it moved back in response to a minimal feedback cue.

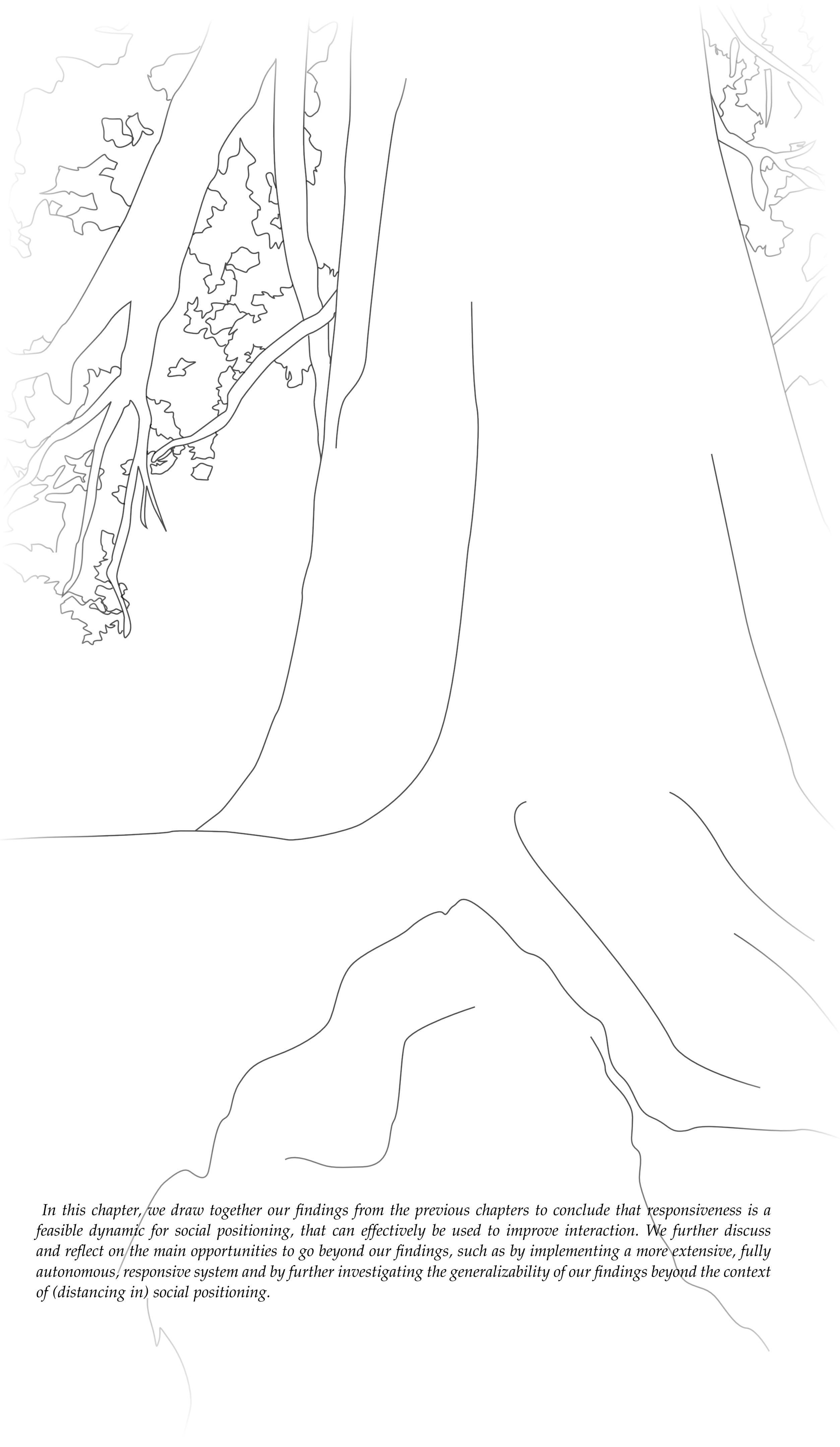
Interestingly, and as a partial answer to our third more exploratory research question, this seems to suggest that setting-specific aspects *and* responsive aspects simultaneously play a role. Yes, we found that participants consider it appropriate if a robot moves back after it got (too) close, agreeing more strongly that it should move further away. And, yes, we also found that participants consider it appropriate if a robot moves back after it got a stronger feedback cue, agreeing less strongly that it should get closer than when a minimal social feedback cue is given.

The main thing counter to those hypotheses, is that participants did not seem to judge it negatively if the robot moved back without 'reason' in terms of getting too close, or getting a strong social feedback cue. In fact, we saw consistently positive judgements of all videos in which the robot used the improvement strategy of moving back. One possible explanation is that participants retro-actively assumed that there had been a social feedback cue from the (external) observation that the robot moved. This explanation is supported by the observation that the robot moving back seemed to influence perception of the robot as having come too close at some point in its approach. If this explanation turns out to be correct, it would add yet another layer to the dynamics of social interaction that could be taken into account.

This opens up possibilities for a range of future work. First and foremost, it would be a logical next step to try and look into real-life first person interactions with a (responsive) system – though doing so would pose the challenges of (1) implementing a full responsive system, and (2) of finding a way to conduct a clean experiment in such a dynamic setting. While this thesis as a whole could provide pointers to help handle both challenges, they are still not resolved. This means we can also not yet be certain if and how our findings would generalize to those cases.

Additionally, it would be valuable to look into an even broader range of improvement strategies – e.g. with different timing, and/or different movement speed (see Box 8). The parameters of the moving back behaviour used in this chapter were mostly chosen for convenience, fitting the capacities of the robot hardware, but the set-up here presented would allow for testing a broader range of improvement strategies.

Overall, we have seen that in this context, both a setting-specific *and* a responsive account of social positioning seem to apply. This suggests that to do full-fledged social positioning, neither normative initial positions nor the social feedback cues of participants should be ignored. In addition, our set-up can be expanded for further research into the dynamics of such social interaction, e.g. to compare different improvement strategies. Our observation that the robot moving back might also retro-actively influence perception of that robot as having come too close, could add a fascinating additional layer of dynamics to the whole. In our next chapter we will discuss the broader implications of these different dynamics that we found.



In this chapter, we draw together our findings from the previous chapters to conclude that responsiveness is a feasible dynamic for social positioning, that can effectively be used to improve interaction. We further discuss and reflect on the main opportunities to go beyond our findings, such as by implementing a more extensive, fully autonomous, responsive system and by further investigating the generalizability of our findings beyond the context of (distancing in) social positioning.

8 CONCLUSIONS AND DISCUSSION

> *I believe that scientific knowledge has fractal properties, that no matter how much we learn, whatever is left, however small it may seem, is just as infinitely complex as the whole was to start with.*
>
> — Isaac Asimov

Throughout this thesis, we have gathered insights into the dynamics of social positioning for a human-sized telepresence robot – into what responsiveness entails, the role it could play in those dynamics, if it is feasible, and if it is effective in generating appropriate behaviour. At the same time, as the quote above also suggests, in doing so we have also uncovered new questions to be answered and things yet to learn. Among this is the fact that, despite discussing responsiveness from various angles, we have not (yet) implemented and evaluated an extensive, fully autonomous, responsive system.

In this section, we will put these findings and insights together and use them to draw broader conclusions. We will first go through the findings from each of the chapters, and use them to answer the main research questions of this thesis (Section 8.1, see Tables 17 and 18 for a schematic overview). In doing so, we will also mention the main limitations to our findings, as well as the main contributions of each of those chapters. We will then give a broader reflection on the questions still left open, discuss the limitations of our findings, and suggest ways in which these questions could be approached (Section 8.2). To conclude, we will look at the impact and implications of our work (Section 8.3).

8.1 CONCLUSIONS AND CONTRIBUTIONS

We started this thesis by giving an intuition of responsiveness, and by roughly identifying the two research questions that have informed the more specific qualitative and quantitative research questions throughout this thesis (Chapter 1):

Research question 1 What are the dynamics that play a role in social positioning?

Research question 2 Can we use responsiveness for effective social positioning?

The first question was more explorative and resulted in the definition of responsiveness as a model for some of the dynamics that we saw play a role in social positioning. The second question then guided an experimental investigation into the feasibility and effectiveness of

Research question 1: What dynamics play a role in social positioning?

1		Static accounts of social positioning "Setting-specific approach"	⇔	Adapting to social feedback cues "Responsive approach"
2	**Approach 1** Theoretical background of social positioning behaviours	• There are many factors that need to be taken into account in static rules for social positioning • ...including the possible combinations of those factors		• Social positioning and other interactions have various dynamic aspects • Various non-verbal cues have been found to play a role in social interactions
3	**Approach 2** Contextual analysis in the context of Teresa	• Reliably detecting the factors influencing appropriateness can be very challenging • There are important individual differences that would not be captured by static general rules		• Social positioning was a rich back-and-forth, e.g. leaning behaviour • The elderly and our other participants used various social signals
4		↪ Setting-specific approach faces various issues in adapting to the temporal and social dynamics of social situations	→	...these issues could be avoided if a robot would use social feedback cues to try and improve its behaviour *through* the interaction ⇓ **Responsiveness is a dynamic that plays a central role in social positioning**

Table 17: Overview of the main findings in Chapters 1-4 of this thesis, as related to our first research question.

	Research question 2: Can we use responsiveness for effective social positioning?			
4	Responsiveness depends on:			
5	**Requirement 1** Can we detect social feedback cues?	•	Detection of feedback information from social cues was significantly better than chance	
		↪	Social feedback information is available from non-verbal behaviours ≀ But better detection will probably be necessary for practical use	✓
6	**Requirement 2** Can we define suitable improvement strategies?	•	Found, within the context of TERESA, that participants preferred a robot to try and accommodate hearing problems, by moving closer or turning up its volume	
		↪	The use of an improvement strategy can be desirable ≀ We also found individual differences in which improvement strategies people preferred	✓
7	**Requirement 3** Should a robot respond to feedback with an improvement strategy?	•	Found that participants perceived it as more appropriate when, in response to a social feedback cue, a robot moved back	
		↪	We confirmed the assumption that people consider it appropriate when a robot responds to social feedback cues ≀ We further saw that people consider it appropriate when a robot moves back after violation of a static norm ('getting too close') and even if it moved back without such violation or feedback – possibly because seeing an agent use an improvement strategy made them assume they missed or saw a social feedback cue	✓
			⇓	
8			**Yes, implementing responsiveness is possible** ≀ Though we cannot yet make strong claims on how challenging or easy it will be to do so. **Yes, we have strong indicators that people consider responsive behaviours appropriate for robots** ≀ ... within the context of social positioning for robots (and possibly beyond). Proof would require implementation and evaluation of a suitable responsive system, for which this thesis can provide a starting point	

Table 18: Overview of the main findings in Chapters 4-8 of this thesis, as related to our second research question

responsiveness in the context of positioning behaviours for a social robot.

In this section, we will discuss the chapters of this thesis in order, drawing out the relevant arguments that allow us to answer these research questions. Chapter 4 serves as a pivot point, introducing both the model that (partly) answers the first research question based on our explorations in the earlier Chapters 2 and 3, while at the same time also making explicit the three main requirements for responsiveness that we then investigate in the subsequent Chapters 5, 6, and 7. A schematic overview can be found in Tables 17 and 18.

8.1.1 *Responsiveness as a key dynamic in social positioning*

We started our explorations into the dynamics of social positioning by investigating the theoretical background in Chapter 2. There we identified, both in work on human-human interaction and in work on human-robot interaction, a general trend from setting-specific approaches, that focused more on static rules governing what a suitable position would be depending on factors in the setting, to more dynamic approaches. We saw that even for the relatively straightforward setting-specific approach of proxemics, there quickly turned out to be an impractically large number of relevant such factors that played a role, both on their own and in combination with each other – from history of pet ownership to the size of a robot. Within the dynamic approaches we found a range of non-verbal cues that people used as, and in response to, social positioning behaviours.

In addition to this broad range of findings, in Chapter 3 we continued our explorations of social positioning, looking at it from the context of TERESA; a semi-autonomous MRP supporting social interaction for the elderly. To do so, we conducted a contextual analysis of social events attended by elderly, a data collection on people controlling an MRP around groups, and an evaluation where elderly used an MRP with autonomous dynamic behaviours over the course of several weeks. Throughout these studies, we saw that social positioning was a rich back-and-forth, in which the elderly and other participants used a variety of social signals. A prime example of this is the observation that the elderly would dynamically lean more or less towards each other during conversations, to accommodate each other's hearing problems. Such a dynamic back-and-forth would be hard to capture in a setting-specific approach – if only because it would be very challenging to reliably detect the presence of hearing problems.

Though not directly related to the main questions of this thesis, these explorations also provide various leads for further investigation into the effects of a semi-autonomous MRP on social interactions (for elderly); from the observation that the controller of the robot often experienced a form of performance pressure, to a dataset on various social positioning behaviours used by people controlling an MRP to interact with subjective judgements of those behaviours by the group members.

Together, as argued for more extensively in Chapter 4, these findings pose various challenges to setting-specific approaches in the context of social positioning, because such approaches try to explicitly reason about the social appropriateness of actions from relevant factors of the setting; (1) there are factors that will not be reliably detectable, such as hearing problems, (2) it will be challenging to consider all relevant factors, let alone consider them all jointly, and (3) it would be hard to capture individual differences in such generalizing reasoning. This is a contribution in its own right, as it makes a limitation of such setting-specific approaches more explicit.

Our findings and theoretical arguments further suggest that these specific issues could be handled by making use of the dynamics of the interaction, if a robot would use social feedback cues to try and improve its behaviour *through* the interaction. We defined the concept of responsiveness to capture the dynamic back-and-forth that this would entail. While it is likely that other dynamics also play a role, such as those captured in the setting-specific approaches we discussed, this provided us with what we set out to find with our first research question: our findings throughout these chapters suggest responsiveness as a dynamic that could play a key role in social positioning.

8.1.2 *An argument for the feasibility and desirability of responsive robots*

When defining the concept of responsiveness in Chapter 4, we also identified (on an abstract level) what would be required to implement effective responsiveness. Since, at the core, responsiveness is the idea of using social feedback cues on previous actions to try and immediately adapt subsequent actions for the better, two practical components are necessary, along with one assumption that needs to be confirmed, respectively:

Requirement 1 Can we automatically detect feedback information from social cues?

Requirement 2 Can we define suitable improvement strategies?

Requirement 3 Do people consider it appropriate for a robot to respond to feedback with an improvement strategy?

We then investigated each of these requirements in order.

In Chapter 5, we collected a rich dataset of the non-verbal reactions of people being approached by a robot, in combination with their subjective suggestions for improvement. On this dataset we then trained and evaluated a classifier that would automatically detect, from the non-verbal reactions (social cues), which subjective suggestions for improvement (feedback information) people gave. This classifier achieved a detection of improvement suggestions clearly and significantly better than chance. Further improvement of the performance would probably still be necessary before this classifier can be of practical use – the collected dataset could provide a starting point for such efforts. Nonetheless, our current findings already show that there is, indeed, social feedback information available from non-verbal behaviours – i.e. it is possible, at least to some extent, to automatically detect social feedback cues (Requirement 1).

In Chapter 6, we looked further into improvement strategies, both by further defining the relationship between social appropriateness and action parametrizations, and through an experiment comparing different ways to accommodate hearing problems. Our theoretical discussion of improvement strategies provides a more complete insight into the things to consider when developing improvement strategies, which can help future implementations of responsive systems. The experiment was conducted with elderly participants in the context of TERESA. It showed that participants in this context indeed preferred a robot to try and accommodate hearing problems – i.e. the use of an improvement strategy can be desirable (Requirement 2). We further found that some participants preferred a robot to use the improvement strategy of turning up its volume, while others preferred a robot to move closer instead. To take such individual preferences into account, it might thus well be desirable for a responsive system to have multiple different 'redundant' improvement strategies available to try and use.

In Chapter 7, we investigated what would be seen as a good 'reason' for a robot to use an improvement strategy (specifically, moving back). This allowed us to test an assumption at the core of responsiveness; that people would think that a robot should use an improvement strategy *in response to* social feedback cues. Our results confirmed this assumption, as participants perceived it as more appropriate when, in response to a social feedback cue, a robot moved back rather than not moving back (Requirement 3). We also saw, in line with the more static accounts of social positioning, that participants considered it appropriate if a robot moved back after 'getting too close'. And, to our surprise, it seemed that participants appreciated it when the robot moved back even when it initially approached to a 'normative distance', without a strong social feedback cue. An intriguing explanation is that seeing an agent use an improvement strategy may have led our participants to assume retro-actively that there was a (stronger) feedback cue; indeed, participants saw the person being approached as being more uncomfortable when the robot used an improvement strategy. Since this experiment was conducted using videos from a third person perspective, it may be that not all these findings generalize to real-life interaction, especially not to situations where people themselves interact with a robot rather than observing such an interaction. However, these findings already align well with those from our experiment on a robot accommodating hearing problems in real-life interaction, which provides a first indication that they at least generalize to some extent.

From these findings on the requirements, we can draw two conclusions related to the second research question.

First, since we have shown that all requirements can be met, we can conclude that it should be possible to implement a responsive system. Our work further can provide a starting point to such an implementation – in the next section, we will look further into how challenging it will be to actually implement an extensive, fully autonomous, responsive system.

Secondly, we found various strong indicators that people consider responsive behaviours appropriate for robots. This already follows from the found positive effects of a robot using (non-autonomous) improvement strategies, but is further strengthened by our finding that after a social feedback cue, using an improvement strategy was regarded more positively than not doing so. It should be noted, though, that our findings to this end have been focused on the context of social positioning – in the next section we will discuss how they might generalize beyond that context.

These conclusions provide a two-part answer to our second research question; yes, it is possible to implement responsiveness for social positioning in a robot, and, yes, it seems that when a robot does so this results in a social positioning dynamic that has a positive effect on the way in which people perceive that robot. In other words, our findings indicate that responsiveness is a feasible dynamic for social positioning, that can effectively be used to improve interaction.

8.2 REFLECTION AND FUTURE WORK

The conclusions above provide first steps for responsiveness, the role it could play in interaction, its feasibility, and its potential effectiveness – and in doing so, they also provide a direction for a range of further steps. These steps are in many ways related to the limitations to our findings; expanding the scope beyond social positioning, implementing and evaluating a more extensive autonomous responsive system, looking into the various limitations to the detection of social feedback cues, and further exploring different improvement strategies.

In this section, we will take a more reflective approach to these further steps and limitations, by further investigating them and looking into ways in which they could be approached in future work.

8.2.1 *Towards implementing responsiveness*

In addition to providing various arguments for the plausibility and the desirability of responsiveness, we have also identified a few of the ways in which the interaction dynamics can still be tough to capture in an extensive autonomous responsive system. Based on these insights we will here take a closer look into what would be required for the development of such a system.

Out of the three requirements for responsiveness established in Chapter 4 – detection of social feedback cues, effective improvement strategies, and the assumed desirability of using improvement strategies in response to social feedback cues – it is the first that we feel has the biggest open challenges. The second and third requirement seem more easily achievable, since the various improvement strategies that we tested all were received positively, possibly simply because they signal a willingness to try and improve (Chapters 6 and 7).

So what are the challenges for reliable detection of social feedback cues? First and foremost, our current attempts have shown that feedback information is present, but there are still many opportunities for improved social signal processing. This specifically includes the challenge of properly handling the inherently temporal nature of social feedback cues: to which action and which action parameter does a given social feedback cue relate? Additionally, based on our findings in the previous chapter(s), social feedback cues may well change dynamically throughout an interaction. For example, people might adapt their social feedback to a robot that seems to ignore their feedback, either by signalling more explicitly and clearly, or by stopping all signalling. Or, the other way around, people might interpret the robot's improvement strategy as social feedback cues and adapt their own behaviours and cues accordingly. Ideally, this would require a form of social signal processing that can accommodate such dynamics.

Besides improved social signal processing for more reliable detection of social feedback cues, we have in this thesis also presented an alternative for handling missing feedback information: adapting the improvement strategy. As discussed in more detail in Chapter 6, a crude form of responsiveness would be for a system to keep trying new behaviours until the available feedback information indicates the agent is doing sufficiently well. The more the available feedback information can be considered as neutral (or lawful) rather than chaotic, the more sophisticated improvement strategies become feasible.

Lastly, it is worth noting that responsiveness need not stand alone; in fact, our findings in Chapter 7 supported both a responsive *and* a setting-specific account of social positioning. This suggests strongly that both approaches should, or at least could, be taken into account when designing social positioning behaviour for a robot.

Taken together, this all suggests that implementations of responsiveness could cover a range of different scopes and ambitions. At its most plain, responsiveness could be a small add-on improving an otherwise setting-specific system, causing an agent to occasionally move back if it suspects based on feedback, or from its own assumptions about social norms, that it might be too close. Or more sophisticated, if that complexity can be achieved, responsiveness could rely on a very detailed and reliable online detection of social feedback cues, allowing an agent to continuously adapt its behaviour in a dazzling and dynamic array of different improvement strategies.

8.2.2 *Beyond social positioning*

Even though our theoretical account of responsiveness is, in theory, generally applicable, the studies in this thesis have focused primarily on (distancing) behaviours in social positioning; so how would our findings generalize beyond that setting? In this relatively simple case, with often 'just' the distance considered as an action parameter, we already found that the dynamics could become quite involved. How would this hold up for more complicated scenarios, e.g. consoling someone who is sad, joining a group of people, or convincing someone to come play a game of squash?

What is more, even if we would assume that responsiveness is generalisable and applicable in such cases, how could we go about actually doing so? Most crucially, there seems to be an inherent conflict between the control necessary in experiments and the richness and broadness of dynamic interaction that responsiveness presupposes.

To start answering these questions, we will first look – once more – at the performing arts. As the various examples throughout this thesis have illustrated, responsiveness is already a well-established (if implicit[1]) concept within the performing arts. The performance comes into existence in the interactions between the setting, the performers – and the audience. Which is why performers commonly use quite a few rehearsals and try-outs to figure out the relevant dynamics of a performance, much like the explorations and iterations in iterative design (see also Box 9).

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1 Despite our best efforts, we have been unable to find a concept that captures responsiveness within the performing arts; it seems the concept is so pervasive and intangible, that it avoids definition. Consider, as an example the **Viewpoints** method – which tries to capture movement in time and space in a set of principles, viewpoints, combined with an approach to investigate those principles in isolation and combination through joint exercises. Key to this philosophy, and these exercises, is a concentrated openness and 'responsiveness' to the environment and the other performers – which permeates the whole method [11]. While there are some components that can be interpreted as capturing parts of what responsiveness entails, e.g. the viewpoint of 'kinesthetic response', it thus seems more fitting to instead see responsiveness as a part of the essence of the method as a whole.

Designing for dynamic interactions

Even for the relatively simple behaviour of finding an appropriate interaction distance, we already found a complex dynamic that we only partially managed to capture in this thesis – so how could one go about designing dynamic behaviours for more complicated social interactions, such as collaborations, or non-verbally inviting people to follow a robot? And what is the potential of such dynamical designs?

One of our project groups took an iterative approach in their attempts to develop non-verbal behaviours for a small robot (the Ollie) that would try and get people to follow it. In doing so, they identified various phases of the interaction – e.g. attracting attention, signalling desire to be followed – and then designed and developed behaviours for each of those phases. This resulted in very dynamic behaviours; for example, they found that it was often effective if a robot would first draw attention, and then move around a corner.

Of interest is also the work of Judith Weda, one of our master students, who investigated how the extent to which a (small, non-humanoid) robot (the Dash) pro-actively contributed to a collaboration influenced the dynamics of the team as a whole. First, she designed the behaviours and validated them in a video study. Then, she tested them in interactions and found that they did indeed influence the team dynamics – but while we thought of the more pro-active behaviours as conducive for good collaboration, we actually found that they caused our participants (30 teams of 2 participants in a 2x1 between-subject experiment) to see their team mates as less effective in problem solving.

These and other explorations into such designs (such as the robotic trash can non-verbally asking for thrash [26]) already result in rich interactions. One important aspect seems to be the use of various iterations in which the different behaviours can be used in interactions with people. And even then the effects of those dynamic behaviours on the interaction dynamics as a whole can still be a surprise.

Box 9: Minimal robot behaviour (1) to support shared leadership in human-robot teams, and (2) to invite people to follow a robot. I had the pleasure of supervising, together with a.o. Cristina Zaga, several students working on dynamical minimal robot behaviours, including Judith Weda who conducted the work on shared leadership as part of her master's thesis [106], and a project group working on follow-me behaviours; Joep Schyns, Jim Tolman, Leonoor Ellen, and Tijmen van Willigen.

From this perspective, it is trivial to find diverse examples that fit our definition of responsiveness; the performing arts cover much more than just social positioning. As per the example that started our introduction, responsiveness seems to play a key role in the difference between expressing righteous anger at someone who is picking her nose, or at someone who cowers in fear. Or what to think of the whole back-and-forth involved in interesting dialogues. There seems to be no reason to assume that responsiveness would not apply to similar real-life settings, even though there the back-and-forth is often established more implicitly. In fact, we have already mentioned a few examples from the literature, such as implicit common ground [74], and the idea of affective grounding [45].

It is worth noting that, in these examples, emotion and personality are not seen as something that is expressed, but rather as something in, or emerging from, the interaction. This is most explicitly the case in the concept of affective grounding, which describes just that [45]. From this perspective, responsiveness could also have the potential to be more than just a tool for behaviour generation; it could be an alternative perspective on how robots (and other agents) can be given emotion and personality.

At the same time, it is just this richness of the dynamics that poses its own challenge; how can we conduct a controlled scientific investigation into this kind of dynamic interaction? In this thesis we have done this in a few ways, by using more exploratory designs (Chapter 3), by looking at aspects of the dynamics in isolation (Chapters 5 and 6), and by compensating with the additional control afforded by a video study (Chapter 7). But while this could provide a starting point, it is still an open question how this can be expanded to richer actual interactions.

Overall, the dynamic captured by responsiveness seems to be generalisable, and apply to interactions above and beyond social positioning. Applying it in those contexts, though, will likely pose its own challenges – because those dynamics seem to be at odds with the control common in scientific investigations. Perhaps we can learn a few things from the performing arts?

8.3 impact and implications

As we have argued through this thesis, if perhaps most explicitly in this chapter, responsiveness is a key dynamic of social positioning – and perhaps even of social interaction in general. It is a dynamic we have seen throughout our investigation of the context, and we have consistently seen positive reactions when our robot would try and improve its behaviour. Or, to make this specific with an example: We have observed elderly lean to each other to accommodate hearing problems, and found that they would like a robot to come closer to the same effect.

In many ways, this idea of responsiveness is not a new concept. As we have mentioned, it is implicit but pervasive in the making of theatre (and in the making of dance). And we have also discussed, in our theoretical overview, several theories that readily fit within the idea of responsiveness. And, as mentioned before, feedback in methods for (online) reinforcement learning plays a role similar to that in responsiveness; suggesting that such methods could well be seen as implementing parts of responsiveness, albeit with the different goal of (finite) learning.

Still, this thesis is the first to explicitly define this concept as a dynamic of social interaction. We expect that this will allow for a more explicit consideration of the added value that responsiveness could have in a variety of contexts. And, as well, for an explicit consideration of when it would be less suitable, such as in situations where 'mistakes' should be avoided at all costs. At the very least, it has allowed us to make the argument that it is desirable for robot social positioning – specifically within the context of TERESA.

We have furthermore demonstrated the importance and potential benefits of taking the back-and-forth into account, which provides an argument for the relevance of responsiveness. Both in social positioning and in the wider range of human interactions, responsiveness seems to be prevalent: we console each other even if we do not know the perfect thing to say, we negotiate to find a solution that works for everyone, and we make the minor adaptations involved in social positioning without much conscious thought. What if such behaviours would also be made available to social robots and other artificial agents? Capturing these dynamics in autonomous systems will, as discussed above, still be a challenge – in terms of scientific methods to look into the important questions, approaches to designing such highly interactive behaviours, and the creation of platforms that provide the necessary components and facilitate responsiveness. But, if our findings are any indication, this challenge of creating autonomous robot responsiveness would be a worthwhile one.

This work provides the first steps towards such autonomous robot responsiveness. Steps that can, hopefully, help inspire people to start making their robots (or agents) more responsive, especially those that do some form of social positioning. Building highly sophisticated forms of responsiveness may as of yet be too challenging, but at its most plain, an implementation of fully autonomous responsiveness need not be far away.

With that, perhaps, one day, robot social positioning can be just one aspect of a rich social back-and-forth – a dance, an interaction.

> An actor and a small blue robot are standing on stage. In between them are several meters of empty floor.

The actor starts talking, "I think my goldfish is quite lonely. For real, just swimming his rounds in his bowl and I have been looking for a day, but he keeps avoiding eye contact. Just swimming his laps." While he is talking, the little robot turns toward him, looks up at him and then approaches. The actor looks at the robot uncertainly, takes a small step back – in turn, the robot stops moving, looks towards the floor. Stealing a few glances at the robot, the actor starts talking again. The same interaction repeats; the robot looks up, approaches, but stops as the actor gets nervous. This time as the actor starts talking again, he turns his upper body slightly towards the robot – as if, despite being nervous, he is talking to the robot. Again the robot approaches, a bit slower this time, and though the actor tenses, he does not step back.

Once more, the actor starts talking. And when he shows the smiley that is tattooed on his hand, he shows it to the robot. The robot looks up, and the actor and the robot look into each other's eyes for the first time. The actor relaxes, looks at the robot almost gratefully. Then he walks towards the robot and picks it up for a hug. It is in that hug that the actor finds his peace.

"Thank you," the actor says, putting the robot back down and leaving the stage.

The small blue robot now stands on the big stage, alone.

It looks around, into the audience. "Hi?" it says. Again it looks around, then it is quiet for a few seconds, barely moving. "Hi?" it tries again, tentatively driving a bit towards the audience. It is quiet for a bit longer, looks around once more, "Hi?". Then, slowly, sadly, the robot lowers its gaze, until it looks at the ground right in front of it.

The audience is quiet, shifting uncomfortably in their seats. And then, as the robot looks into the audience one last time, an audience member in the front rows gets up. She runs onto the stage, she picks up the robot, and she gives it a warm hug.

— "Connectors", a scene with Dash,
performed July 7th, 2016

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2013

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2017

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2018

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19 Minh Duc Pham (VUA) *Emergent relational schemas for RDF*
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21 Aad Slootmaker (OUN) *EMERGO: a generic platform for authoring and playing scenario-based serious games*
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23 Kim Schouten (EUR) *Semantics-driven Aspect-Based Sentiment Analysis*
24 Jered Vroon (UT) *Responsive Social Positioning Behaviour for Semi-Autonomous Telepresence Robots*

But there's no sense crying
over every mistake.
You must keep on trying
'til you run out of cake.
And the science gets done.

— Portal
Still alive
Jonathan Coulton

Propositions, supplemental to the PhD Thesis

RESPONSIVE SOCIAL POSITIONING BEHAVIOUR

for semi-autonomous telepresence robots

Jered Vroon

1. It is impossible to fully capture in general rules what behaviours an individual will perceive as appropriate.
   To think the results of quantitative experiments can be readily applied to individuals, is to be prejudiced. To think that any static set of laws or regulations will always be just, is to be naive.

2. People signal what behaviours they perceive as appropriate through the social feedback cues in their (non-verbal) behaviours.
   As demonstrated in the thesis, this proposition holds for the way in which people respond to a robot's distancing in its approach behaviour.

3. Adapting to social feedback cues – responsiveness – will help social robots find appropriate behaviour *through* the interaction.
   Attempts of a robot to improve its behaviour can have a positive effect on how that robot is perceived. As demonstrated in the context of the thesis, people consider it as more appropriate when a robot adapts to social feedback cues, as opposed to when it does not.

4. The development of general approaches to creating social robot behaviours will help the field of Human-Robot Interaction mature.
   There are currently more approaches to generating social behaviours in the performing arts than in the field of human-robot interaction. While the currently available design recommendations and robot-specific solutions provide an important starting point, there are still too few general theories and models to guide the efficient creation of suitable social robot behaviours.

5. You can complete a PhD in social robotics without any social skills.
   To develop social behaviours for robots is more contingent on open investigation and modeling, than on the posession of intuitive social skills – in fact the latter might even be detrimental to the former.

6. Each failure means you have learned something new, iff you had reason to expect success.
   You can only grow as a person by doing new things you could fail at.

7. It is impossible to fully capture the meaning of your life in general rules, you can only find it through your own interactions with the world.
   Or, in the words of Viktor Frankl: "Life ultimately means taking the responsibility to find the right answer to its problems and to fulfill the tasks which it constantly sets for each individual."

Stellingen, behorende bij het proefschrift

RESPONSIVE SOCIAL POSITIONING BEHAVIOUR

for semi-autonomous telepresence robots

Jered Vroon

1. Het is onmogelijk om in algemene regels te vatten welk gedrag een individu als gepast zal beschouwen.
Te denken dat de resultaten van kwantitatieve experimenten direct kunnen worden toegepast op individuen zou een vooroordeel zijn. Te denken dat wetten of regels altijd juist zullen zijn is naïef.

2. Aan de (non-verbale) reactie van mensen kunnen we zien welk gedrag ze als meer of minder gepast beschouwen.
Zoals we hebben gedemonstreerd in het proefschrift houdt deze stelling in elk geval voor de manier waarop mensen reageren op de afstand die een hen benaderende robot gebruikt.

3. Het aanpassen van gedrag aan de hand van reacties van mensen – 'responsive' zijn – zal robots helpen om gepast gedrag te vinden, míddels de interactie.
Als een robot probeert om zijn gedrag te verbeteren, dan kan dit een positief effect hebben op hoe die robot wordt gezien. Zoals gedemonstreerd in de context van dit proefschrift, zien mensen het als meer gepast wanneer het gedrag van een robot wordt aangepast aan de hand van de reacties van mensen.

4. Ontwikkeling van algemeen toepasbare methodes om sociaal gedrag voor robots te creëren zal het veld van Mens-Robot Interactie helpen tot wasdom te komen.
Er zijn, momenteel, meer methodes voor het creëren van sociaal gedrag in de uitvoerende kunsten dan in het veld van Mens-Robot Interactie. Al bieden de beschikbare aanbevelingen voor het ontwerp van zulk gedrag en oplossingen voor specifieke robots een belangrijk beginpunt, er zijn nog steeds te weinig algemene theoriën en modellen voor de efficiënte ontwikkeling van passend sociaal gedrag voor robots.

5. Je kunt een PhD in de sociale robotica afronden zonder enige sociale vaardigheden.
Voor het ontwikkelen van sociaal gedrag voor robots is het belangrijker om onbevooroordeeld te onderzoeken en modelleren, dan om een intuïtie voor sociaal gedrag te hebben – zo een intuïtie zou het zelfs moeilijker kunnen maken om onbevooroordeeld te zijn.

6. Elke mislukking is een nieuwe les, mits je reden had om succes te verwachten.
Je kunt enkel groeien door het doen van nieuwe dingen waar je fouten in kunt maken.

7. Het is onmogelijk om in algemene regels te vatten wat de zin is van je leven, die is alleen te vinden door de interactie met de wereld aan te gaan.
Of, in de woorden van Viktor Frankl; "Leben heißt letztlich eben nichts anderes als: Verantwortung tragen für die rechte Beantwortung der Lebensfragen, für die Erfüllung der Aufgaben, die jedem einzelnen das Leben stellt, für die Erfüllung der Forderung der Stunde."