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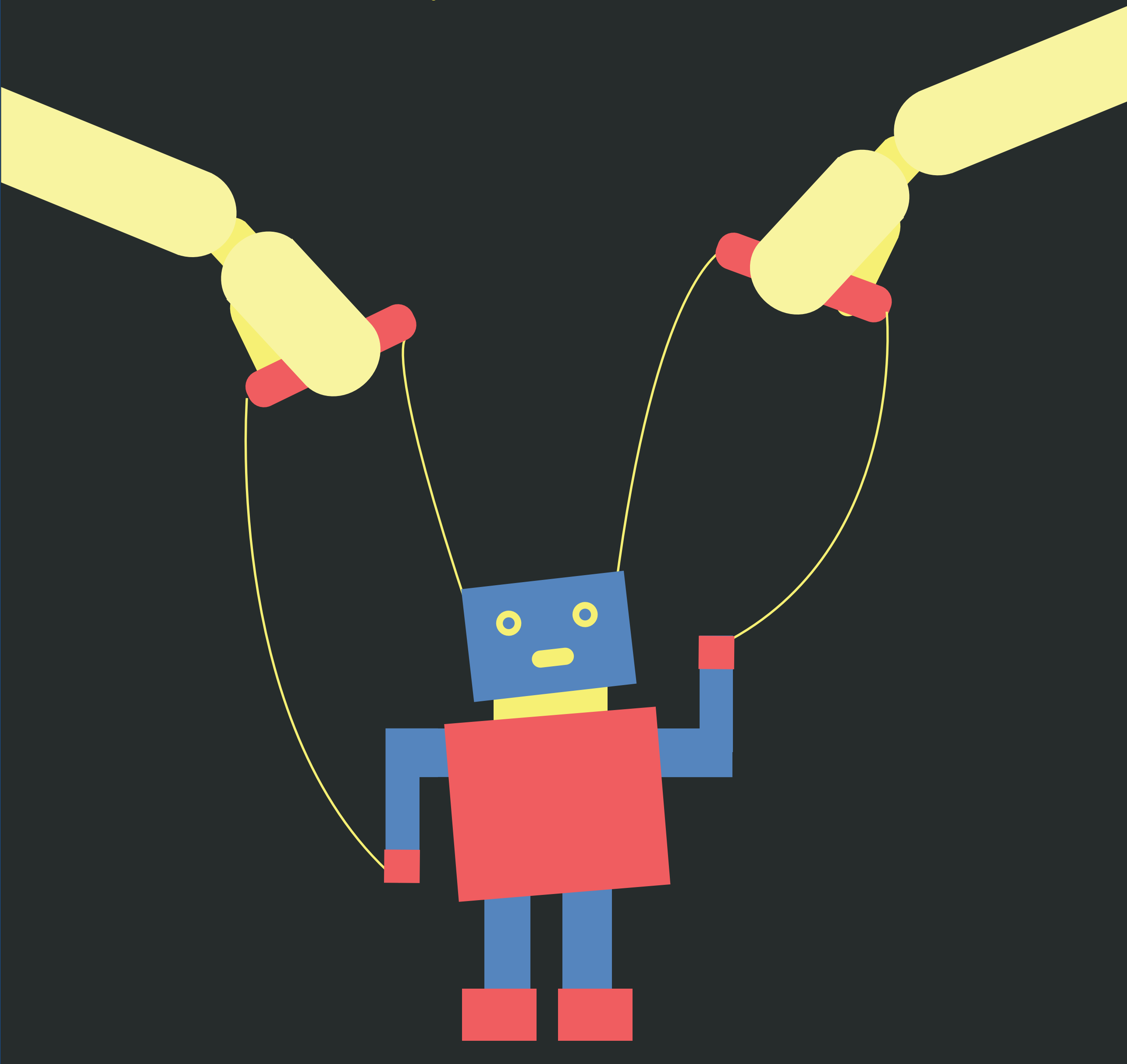

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Designing Social Cues for *Effective* Persuasive Robots

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Summary

The development of robots that are capable of acting as social interaction partners has increased dramatically in recent years. The possibility emerges to use these social robots as persuasive agents to support attitude and behaviour changes. To guide the design of social robotic technology, research needs to study how social cues displayed by persuasive robots influence the way people experience interactions and the extent to which they comply with the persuasive attempts. However, people can react in very different ways towards these attempts. Potential negative responses include psychological reactance which gives rise to negative feelings and thoughts and may reduce compliance and trust towards the persuasive robots. On the other hand, people may like the persuasive attempts by such robots causing them to comply. The research presented examines how to design social cues for persuasive robots so that persuasive attempts will be effective (high compliance and high acceptance) and positively perceived by humans (low psychological reactance, high trusting beliefs and high liking) in decision-making situations. In line with the Media Equation hypothesis (Reeves & Nass, 1996), we expect social responses towards persuasive robots (the social actors) to be analogous to social responses towards human persuaders.

The first part of the thesis investigates social responses triggered by different numbers of social cues implemented on persuasive robots. First, we assessed how people respond to a robot that has different numbers of social cues by evaluating the resemblance of the robot (with its social cues) to the representation of a real person and evaluating the robot's living creature likeness. Results showed that people perceive a robot with a combination of all social cues: emotional intonation voice, head movement, and facial expression as most resembling a real person and having the highest likeness to a living creature (presented in Chapter 2). However from this preliminary study, it was still unclear whether these social cues trigger the social reactions in persuasive attempts. Thereby in Chapter 3, we studied when reactant responses to artificial agents occur in persuasion. That is, the influence of the number of social cues and the coerciveness of the language used by persuasive agents on psychological reactance and compliance responses were investigated. Results suggested that when the agent used slightly coercive language, the more social cues it displayed, the more psychological reactance its user experienced. In contrast, when the agent used highly coercive language, the agent without social cues (advisory-text) caused the highest psychological reactance whereas a robot that displayed some social cues (minimal or enhanced social cues) elicited lower psychological reactance. Additionally, results showed that the stronger the coercive language of the persuasive agent, the more the user complied, independent of the number of social cues displayed by the persuasive agents. Nevertheless, this study provided no evidence in support of the Social Agency theory (Mayer, Sobko, & Mautone, 2003), which would expect that people respond in more social ways (i.e., show more psychological reactance) when a social robot displays stronger (or more) social cues in delivering highly coercive persuasive message. We argue that for this effect to occur, people need to be (more) involved in the task at hand. Confirming our proposal, a study presented in Chapter 4 thereby showed that a social robot presenting more social cues caused

more social responses (psychological reactance and compliance) especially when people care about the task. That is, a persuasive robot with more social cues caused higher psychological reactance and this effect was stronger when the user felt involved in the task at hand. Also, higher task involvement caused lower compliance, especially when the appointed advisor was a robot with enhanced social cues. In investigating the appropriate number of social cues for persuasive robots in achieving low psychological reactance and high compliance, results in Chapter 5 suggested that a robot with minimal social cues (neutral face and blinking eye) invoked a lower psychological reactance in comparison to the robot with enhanced social cues (emotional intonation voice, head movement and facial expression) and advisory-text social agents.

Despite psychological reactance and compliance, evidence suggested that trust in robotic interaction partners is crucial so that people can rely on persuasive robots for physical and even emotional support. The second part of the thesis investigates the characteristics of social cues implemented into persuasive robots to instigate social responses. In this part, we explored two types of social cues that persuasive robots have to gain human trusting beliefs, compliance and to trigger less psychological reactance during the persuasive attempts. In Chapter 6, we studied the influence of *non-interactive social cues* on social responses to the persuasive robots. Inspired by recent research in interpersonal psychology, results presented in this study demonstrated that persuasive robots with upturned eyebrows and lips facial characteristics besides match the gender of the user caused lower psychological reactance. Also, results showed that persuasive robots with upturned eyebrows and lips facial characteristics caused higher trusting beliefs and higher compliance, independent of the gender of the persuasive robots. Moreover, liking is shown to have a mediating role in enhancing trust and reducing psychological reactance towards persuasive robots. The design for likeable robots could be achieved by simpler means such as the static external appearance of the robots. Nevertheless, Chapter 6 provided no evidence that the interactive social cues of the robots mattered. We argue that interactive social cues could be advantageous especially for social robots in persuading people. Therefore, in Chapter 7 we examined the influence of *interactive social cues* that the persuasive robots have on human psychological reactance, compliance, trusting beliefs and liking. Overall, results showed that the more the persuasive robots displayed interactive social cues (head mimicry and proper timing for praises), the more people like the robots and the less psychological reactance its user experienced. Also, praise independent of its timing, enhanced trusting beliefs. We also found that interactive social cues provided no evidence for the improvement of compliance.

Lessons learned based on human social responses towards social cues displayed by persuasive robots have triggered a formulation of acceptance model for persuasive robots presented in Part 3. In Chapter 8, we presented an acceptance model aiming to (1) integrate the model of functional acceptance (TAM) with a model of social acceptance (based on social responses) towards persuasive robots (2) test whether social responses are one of the key determinants for people to accept the persuasive robots. Using partial least square (PLS) structural equation modelling (SEM) method, results showed that adding trusting beliefs and liking as key determinants to the TAM model significantly improving its predictive power. No contribution of psychological reactance in predicting the acceptance of persuasive robots was found; this could be because the robot was endowed with likeable social cues which caused users experienced little psychological reactance. Compliance was also not a predictor for the acceptance of persuasive robots.

As concluded in Chapter 9, studies presented in this thesis shed light on the design of robots as seamless persuasive systems and highlight the importance of considering social responses in human-robot persuasive interaction. Specifically, this thesis provides insight that persuasive robots which used highly coercive language with minimal and likeable social cues: most trustworthy face characteristics, head mimicry and proper timing for social praises contribute to positive social responses: low psychological reactance, high trusting beliefs, high compliance and /or high liking. Social responses especially trusting beliefs and liking are the key determinants for people to accept the persuasive technology (social robots) to be used in their daily life.

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CHAPTER 1

Introduction

1.1. General Background

Social (or sociable) robots are designed to engage people in an interpersonal manner for achieving positive outcomes as partners, mediators of the interaction, or co-workers (Breazeal, Dautenhahn, & Kanda, 2016). In the near future, social robots are expected to play an increasingly important role in our lives. Robots will not only be used for repetitive works and in physical tasks as currently in the manufacturing sector (Prassler, Bruyninckx, Nilsson, & Shakhimardanov, 2009) but also in domains that require social interaction skills (Breazeal, 2004; Kopp, Gesellensetter, Krämer, & Wachsmuth, 2005). Social robots can be used to assist humans in daily life and might linger most of the time in the vicinity of humans, comparable to smartphones nowadays (Eguchi & Okada, 2018; Share & Pender, 2018). Imagine at the beginning of your day, a robot waking you up sharp at 7 o'clock in the morning for work, suggesting you to have healthy food for lunch, and reminding you to take your medicine before going to bed.

To interact and accompany humans, social cues of the robots are critically important. When people designing social robots like Geppetto made Pinocchio, Geppetto included social cues to make Pinocchio more alive and perhaps, more persuasive. Social cues are defined as indirect communication that expresses thoughts or intentions of social actors (the Pinocchio, and in our case the persuasive robots) verbally as well as nonverbally. Social cues in persuasive technology like robots are known to trigger social interaction with humans (Fogg, 2002; Sauppé & Mutlu, 2014). Fogg (2002) categorized five primary types of social cues as physical, psychological, language, social dynamics, and social roles. Examples of social cues include body movements (physical), feelings of empathy (psychological), spoken language (language), responding to questions (social dynamics) and roles of the social actors such as a competitor (social roles) (Fogg, 2002).

Research has found that social cues by robots can bring positive and negative interaction experiences. Positive experiences include social engagement with robots (Moshkina, Trickett, & Trafton, 2014; Perugia et al., 2017), the effectiveness of the social actor in delivering messages (Katevas, Healey, & Harris, 2015; Pu, Moyle, Jones, & Todorovic, 2018), the degree to which people perceive the robot as an intelligent agent (Talamas, Mavor, Axelsson, Sundelin, & Perrett, 2016), the value of anthropomorphism (Duffy, 2003), and social acceptability of a robot (De Graaf & Allouch, 2013; Heerink, Kröse, Evers, & Wielinga, 2010b). David, Costescu, Matu, Szentagotai, and Dobrean (2018) showed that gaze orientation, pointing and vocal instruction by Nao robot increased engagement of the children with autism spectrum disorder. Gaze and head gesture also have been shown to have a positive impact on learning performance in several studies (Andrist, Mutlu, & Tapus, 2015; Mwangi, Barakova, Díaz-Boladeras, Mallofré, & Rauterberg, 2018; Willemse, Marchesi, & Wykowska, 2018). Another example like Goble and Edwards (2018) demonstrated that a robot which used vocal fillers like "umm" and "hmm" increased human perceptions of social presence of the robot, as compared to a robot not using vocal fillers. Others like Saerbeck, Schut, Bartneck, and Janse (2010) demonstrated that verbal and non-verbal actions of a robot increased learning performance and concentration of the students in teaching second language skills. Another study conducted by Straten et al. (2018) found that expressive intonation and humanized bodily appearance of a robot have an effect on children's positive engagement. For health self-management of older adults application, Looije, Neerincx, and Cnossen (2010) found that social robots (physical and virtual characters) with high-level dialogue, natural cues, use of emotions, and social dialogue were more empathic and trustworthy than the text-based assistant. In contrast, negative or neutral experiences in human-robot interaction include negative attitudes (Tatsuya et al., 2016) and the feeling of anxiety (Nomura et al., 2006) towards robots. For instance, Kennedy, Baxter, and Belpaeme (2015) highlighted the negative implications of social cues on tutor robots in supporting learning opportunities for children. That is, social behavior displayed by the robot (e.g., gaze and iconic gestures) caused distraction to the children during the learning process. The children focused more on the social robots rather than concentrating to the lesson content. As results, learning gains of the children in less sociable robots condition was higher than the children in more sociable robot condition. Similarly, Rosenthal-von der Pütten, Krämer, and Herrmann (2018) found that robot-specific nonverbal behavior (behavior which is impossible to be displayed by humans) such as changing the colors of the Nao robot's eyes in expressing different emotions using LEDs has no significant influence on the participants' emotional state, their perceived intelligence and likeability towards the non-human-like robot compared to the robot with human-like nonverbal behavior. Palinko et al. (2015) summarized the advantages and drawbacks of using gaze in tutoring robot.

As suggested by Langer (1992), people socially connect with robots on a subconscious level. Providing evidence for this proposal, research by Reeves and Nass (1996) showed that people also interact with non-living things such as computers with simple social cues as similar interaction as other human beings. Similar to computers, we expect that a robot with a humanoid face (the social actor) will get the same treatment that people would get. Thus, we argue that the interaction with social robots is more in line with human-human interaction rather than human-technology interaction. This argument is supported by earlier research (Ham, Bokhorst, Cuijpers, van der Pol, & Cabibihan, 2011; Heerink, Krose, Evers, & Wielinga, 2007). With advances in robotic designs, social robots take on an increasingly complex array of social roles as social actors in creating relationships with humans.

The growing interest in social robotics makes it relevant to examine the potential of robots as persuasive technologies. Earlier studies demonstrated that social robots can play an important role in persuading people (Herse et al., 2018; Rincon, Costa, Novais, Julian, & Carrascosa, 2018; Salomons, van der Linden, Strohkorb Sebo, & Scassellati, 2018). For brevity we refer to such robots as *persuasive robots*. Persuasive robots have been employed in broad range of applications for instance as an assistant to elderly community (Rincon et al., 2018) and providing recommendations in several decision-making tasks like helping people to choose food (Herse et al., 2018) and movies (Rossi, Staffa, & Tamburro, 2018). Research in social robotics has elaborated on this theme, producing a wealth of knowledge regarding social responses to persuasive robotics.

The term *persuasion* refers to attempts in influencing people to do or to believe something, which causes the persuadees to changing their attitudes, behaviors or thoughts (Fogg, 2002; Kaptein, Markopoulos, de Ruyter, & Aarts, 2010) without using force or trick (Cialdini, 1993; Seiter, Gass, & Education, 2004). In persuasion context (just like in all communication), a successful communication process can be achieved through four important elements; the sender (persuader), the receiver (persuadee), the context (content of the conveyed message), as well as the channel (used in delivering the message) and all of them must fit in their roles accordingly (Braddock, 1958; Oinas-Kukkonen & Harjumaa, 2008). Earlier research suggested that the extent to which people experience and show responses seems to be dependent on various factors including source and message characteristics. For example, the type of role of the persuader seems crucial, just like the persuader's character, (e.g., is the persuader rude or pleasant?) How is the message conveyed? Is it communicated through implicit or explicit language? What is the communication channel used, for example is it face-to-face or through a mediator? (Roubroeks, Ham, & Midden, 2011; Salacuse, 2015). Earlier research (Ruhland et al., 2015; Siegel, Breazeal, & Norton, 2009; Stevens et al., 2016) also showed that social cues are one of the important elements in successful persuasion activities.

To date, several studies have investigated the effect of social cues by persuasive robots on human responses. For example, an earlier research by Ham and Midden (2014) found that social feedback such as compliments provided by a persuasive robot has stronger persuasive power than factual feedback provided by a visual element of an interface. Others like Ham, Cuijpers, and Cabibihan (2015) provided evidence that gaze by a persuasive robot increased the persuasiveness effect on storytelling as compared to a persuasive robot with gestures only. An example of gender serving as a social cue is a study by Siegel, Breazeal and Norton (2009) which demonstrated that humans chose persuasive robots that have dissimilar gender with the participants as more trustworthy and credible compared to the robots with similar gender. Nonverbal cues such as proximity (within vs. outside the personal space), gaze (dynamics vs. static), and gestures (robot's arm movements during speech: with gesture vs. no gesture) also improved compliance towards persuasive robots as shown in an earlier study (Chidambaram, Chiang, & Mutlu, 2012).

With gradual emergence of social robots in our life, development of persuasive robots that are well accepted by people is essential. More recently, special attention has been paid to the social responses to persuasive robots. Several acceptance models for example Technology Acceptance Model (TAM) (Davis et al., 1989) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) were employed to predict the acceptance of social robots in earlier studies (De Graaf & Allouch, 2013; Shin & Choo, 2011; Young, Hawkins, Sharlin, & Igarashi, 2009). However, these model of acceptance do not yet help us to understand the key determinants for people to *accept* robots as persuasive agents. There are still many unanswered questions about human acceptance of persuasive robots, which lead us to understand the relative impact of social cues by that robots and the extent to which the robots evoke social responses. Additionally, it is important to include social responses in the acceptance model because establishing the importance of various factors (e.g. reactance) for acceptance can guide future research (e.g. should we keep using reactance, or trust, or liking as outcome variables in experiments).

In this thesis, we focus on designing a robotic persuader by investigating the effects of different numbers and characteristics of social cues on human social responses. Based on five main categories of social cues highlighted earlier (Fogg, 2002), we investigate the effect of social cues of the persuasive robots on social responses in six experimental studies. We use the robot in the role of advisor by providing advice to the participants in decision-making tasks. We only focus on persuasive attempts for thought change.

In line with the Media Equation hypothesis (Reeves and Nass, 1996), we expect that social responses towards our social actors, the persuasive robots, to be analogous to social responses towards human persuader. Earlier research by Chidambaram, Chiang and Mutlu (2012) as well as Fox, Ahn, Janssen, Yeylekis, Segoia and Bailenson (2015) showed that social responses towards the robots could be enhanced when the persuasive robots exhibited social cues.

However when humans are confronted with a strong persuasive attempt either by other humans or robots, they may perceive it as threatening towards their freedom in making decisions, which can result in *psychological reactance* (Brehm, 1966; Brehm & Brehm, 2013). Psychological reactance may be manifested in people's behavior causing them to not *comply* or even *do the opposite* than what is requested by the persuasive robots. Indeed, psychological reactance may also lead to irrational behaviors and thoughts aimed to re-establishing individual freedom (Quick & Stephenson, 2007b, 2008) for example having a feeling of *distrust* towards the persuasive robots. On the other hand, principles of persuasion highlighted that humans more likely to comply to the persuasive attempts made by someone (in our case the persuasive robots) they *like* (Cialdini & Cialdini, 2007). Due to the social responses that might be triggered due to persuasive attempts, this thesis examines specific social responses towards persuasive robots: psychological reactance, compliance, trusting beliefs and liking. Additionally, we also propose a technology acceptance model for persuasive robots in our final experimental study.

In this Introduction chapter, we first describe the theoretical frameworks employed as guidelines to understand human social responses to persuasive robots. Then, we present an overview of research questions in the next subsection by discussing the way each empirical chapter contributes to connect these research areas. We end this chapter by summarizing the research approach used in designing our studies and the key contributions of this thesis.

1.2. Theoretical frameworks

This section elaborates the main theoretical frameworks related to the experimental studies presented in this thesis.

Many research paradigms used in social robotics area (Booth, Tompkin, Waldo, Gajos, & Nagpal, 2017; Chang, Lu, & Yang, 2018; Edwards, Edwards, Westerman, & Spence, 2018) took advantage of the Media Equation hypothesis (Nass & Moon, 2000; Reeves & Nass, 1996) by viewing persuasive robots as social actors. The Media Equation hypothesis (Reeves & Nass, 1996) highlighted that people unconsciously and automatically responded to the social actors (in our case the persuasive robots) which have human-like behaviors similar to the way they responded to other human beings; even when they were perfectly aware that the social actors are machines. The Media Equation hypothesis (Reeves & Nass, 1996) also suggested that simple human-like behaviors like taking turns during the interactions were sufficient to elicit social responses, independent of the number of social cues applied to the social actors. That is, people required a simple cue (instead of multiple cues at a time) to respond socially towards these social actors.

Later on, Social Agency theory (Mayer, Sobko, & Mautone, 2003) was proposed based on the Media Equation hypothesis (Reeves & Nass, 1996) and Social Cues theory in multimedia learning (Moreno & Mayer, 2000). Social Agency theory (Mayer et al., 2003) claimed that people prompted to interpret the social actors with stronger social cues as social interaction partners (e.g., interaction with a real human), nonetheless interact with social actors with weaker social cues as information senders (e.g., interaction with a text). The interpretation towards social actors with stronger social cues as social interaction partners then encouraged to higher social responses by humans. In evaluating students' performance using multimedia learning, a study by Mayer et al. (2003) concluded that using human-like features as social cues like human voice elicited higher rating on social dimensions than the less human-like social cues such as a machine voice. This study also showed that students performed better when multimedia message used human voice with standard accent compared to foreign accent. This theory was supported by Social Cues hypothesis (Louwerse, Graesser, Lu, & Mitchell, 2005) and earlier studies in several contexts (Atkinson, Mayer, & Merrill, 2005; Barakova, De Haas, Kuijpers, Irigoyen, & Betancourt, 2018; Roubroeks et al., 2011).

Other theories like Theoretical Model of Social Influences (Blascovich, 2002b) pointed out that the social influence of virtual others (the interaction partners in virtual environments) is determined by the level of social agency and the level of behavioral realism of the social agents. In this theory, social agency refers to the extent in which people perceive an agent (the virtual others) as the representation of a real person in real time. Behavioral realism refers to the extent in which the agent (the virtual others) is anticipated to portray some social interaction behaviors as expected by humans based on previous experiences (Blascovich, 2002a). For example, people would expect some verbal cues (e.g., talk) from virtual others that has a mouth. For purposeful social influences like in persuasive attempts, this theoretical model suggested that higher agency and higher behavioral realism of a virtual others triggered higher social responses from the users (Guadagno, Blascovich, Bailenson, & Mccall, 2007).

Based on the mindless state of humans in controlling their social responses when observing robots' social behaviours (Langer, 1992), we identify an overlap between the Media Equation hypothesis (Reeves & Nass, 1996), the Social Agency theory (Mayer et al., 2003) and the Theoretical Model of Social Influences (Blascovich, 2002b). Specifically, the Media Equation hypothesis (Reeves & Nass, 1996) suggests that a simple social cue is sufficient to elicit social responses. However, the Social Agency theory (Mayer et al., 2003) suggests that adding human-like social cues (human voice with standard accent vs. human voice with foreign accent vs.

machine voice) led to higher performance in multimedia learning. Based on this theory, we also expect that more social cues can cause more social responses in persuasive attempts by robots. Consistent with the Social Agency theory (Mayer et al., 2003), the Theoretical Model of Social Influences (Blascovich, 2002b) suggests that adding more social cues like eye movement to an agent (in our case the persuasive robots) that has eyelid and body movement (walking, etc.) increases the behavioral realism of the social actor, which in turn results in higher social responses from users than an agent that displays only one social cue at a time. However, the Media Equation hypothesis (Reeves & Nass, 1996) and the Social Agency theory (Mayer et al., 2003) leave open the question whether persuasive attempts by persuasive robots with higher social agency (stronger or more social cues) will be more effective and perceived more positively by humans than attempts by persuasive agents with lower social agency (weaker or fewer social cues). The Social Agency theory (Mayer et al., 2003) also proposed to use human-like features as social cues in triggering positive social responses. These features excite humans to respond socially to the robots as claimed by Theory of Anthropomorphism (Epley, Waytz, & Cacioppo, 2007) and Social Cues hypothesis (Louwerse et al., 2005). However, these theories and hypotheses also leave open another question: which human-like features will be effective and perceived positively by humans in persuasive attempts by robots?

As shown earlier, there is an impressive number of studies on social cues for social robots. However, earlier research has not yet investigated which social cues will increase the effectiveness and positive perceptions towards *persuasive attempts* by robots. Based on earlier research (Cialdini & Cialdini, 2007; Roubroeks, Midden, & Ham, 2009), we argue that the *number* and the *characteristics* of social cues displayed by persuasive robots trigger different social responses. Thus, in this thesis, we are interested to investigate *the number* and *the characteristics* of social cues that trigger low psychological reactance, high compliances, high trusting beliefs and high liking towards the persuasive attempts by robots. Also, we are interested to investigate the *roles of social responses* towards persuasive robots for determining the acceptance of such robots to be used in daily life.

Overall, this thesis presents six scientific studies dedicated to answer one overarching research question and five research questions as presented in the next section.

1.3. Structure of the thesis

In summary, this thesis aims to bridge the gaps between the theoretical frameworks for example between Media Equation hypothesis (Reeves & Nass, 1996), Theoretical Model of Social Influences (Blascovich, 2002b) and Social Agency theory (Mayer et al., 2003) and enriching the literature regarding social responses towards social cues implemented on persuasive robots. The overarching research question for this thesis is:

Overarching Research Question:
How to design social cues for persuasive robots so that the persuasive attempts will be effective, and positively perceived by humans?

To investigate this overarching research question, the effectiveness of persuasive attempts in this thesis is accessed by evaluating the compliance and the acceptance towards the persuasive robots. People's perception of social cues will be assessed by evaluating their psychological reactance, trusting beliefs and liking towards the persuasive robots.

To answer this overarching research question, we divide this thesis into three parts. The **first** part of the thesis investigates social responses triggered by different *number of social cues* implemented on persuasive robots. The **second** part of the thesis investigates social responses triggered by different *human-like characteristics of social cues* implemented on persuasive robots. Meanwhile, the **third** part of the thesis investigates the roles of social responses in predicting the *acceptance of persuasive robots*. Details for each part will be elaborated in the following paragraphs.

Part 1 of the thesis aims to test Social Agency theory (Mayer et al., 2003). We investigate whether an agent that has stronger (or more) social cues will cause people to respond more socially (more persuasive) than an agent that has weaker (or less) social cues. However before answering the overarching research question, we need to answer a preparatory question, in which we evaluate humans' perception of social agency of SociBot in displaying different sets of social cues (presented in **Chapter 2**). The perception of social agency of SociBot is important in this thesis since we expect that higher agency will trigger higher social responses from the users as suggested by Theoretical Model of Social Influences (Blascovich, 2002b). As described before, earlier research (Guadagno et al., 2007; Matsui & Yamada, 2017) have provided support for this theory without studying whether more social cues (with higher social agency) lead to stronger persuasive power. Later in Chapter 3, we investigate that issue. To be able to study the relationship between the number of social cues and a robot's persuasive power, we first need robots with different levels of social agency. Therefore, in **Chapter 2**, we evaluate how people respond to a robot that has different number of social cues: We investigate participants' social agency judgments of robots with only individual, or pairs or combinations of three social cues.

> **Research Question 1.1:**
> *Which social cues should a robot have so that people perceive the robot as the most representing a real person and the highest likeness to a living creature?*

Based on the results of the first study, social cues which humans perceive as the most representing a real person and resulting in the higher likeness to a living creature are implemented in the highest social agency condition for persuasive agents in the following studies.

To attain the aim of Part 1 in testing whether an agent that has more social cues is also more persuasive, we assess the participants' compliance to its requests and the extent to which the participants experience psychological reactance towards persuasive attempts in **Part 1**. We manipulate the number of social cues in three social agency conditions: no social cues (low social agency) vs. minimal social cues (medium social agency) vs. enhanced social cues (high social agency) in the studies presented in **Chapter 3, Chapter 4, and Chapter 5**.

Research Question 1.2:
What is the influence of the number of the social cues used by persuasive robots on the user's psychological reactance and compliance responses?

In earlier research of psychological reactance (Roubroeks et al., 2011), the coerciveness level of the language used by the persuader was used to trigger reactance. Confirming that persuasive agents (not robots) can likewise cause reactance when using highly coercive language, Roubroeks and colleagues (2011) also showed that higher social agency of the persuader leads to higher psychological reactance. However, their study begets the question whether these conclusions hold during actual interaction with an embodied agent as a persuader rather than merely when being confronted with a picture or video-clip thereof as in (Roubroeks et al., 2009). Accordingly, besides the number of social cues, in the current study (presented in **Chapter 3**) we also manipulate the coerciveness level of the language used by the persuasive robot (slightly coercive language vs. highly coercive language), to make sure it triggers reactance.

Research Question 1.2 (a):
What is the influence of the number of the social cues and the coerciveness of language used by persuasive robots on the user's psychological reactance and compliance responses?

We expect that participants will experience higher psychological reactance and lower compliance when receiving advice from an agent with more social cues (than an agent with less social cues) expressed in highly coercive language than when receiving advice in slightly coercive language from the same agent.

Other than coerciveness of language, earlier studies (Johnson & Eagly, 1989; Oreg & Sverdlik, 2014) suggested that people respond differently to persuasive attempts depending on their level of involvement on the related topic. Nevertheless, earlier research has not yet examined the effect of involvement upon of reactance. Crucially in **Chapter 4**, we study whether higher involvement of the participant leads to more reactance and lower compliance especially when a robotic persuader has more social cues. Thus, in addition to the number of social cues, we also extend the second research question by manipulating the level of involvement towards the task assigned in the next study (involvement: low vs high).

Research Question 1.2 (b):
What is the influence of the number of social cues and the task involvement used by persuasive robots on the user's psychological reactance and compliance responses?

We expect that participants will experience higher psychological reactance and lower compliance when receiving advice from higher social agent (than lower social agent) in high involvement issue (than in low involvement issue).

Finally, to find the appropriate number of social cues for persuasive robots so that the effectiveness of persuasive attempts could be increased (high compliance) and positively perceived (low psychological reactance) by humans as proposed in our overarching research question, we combined (in **Chapter 5**) the datasets of studies from **Chapter 3** and **Chapter 4** that has the same hypothesis.

After studying in **Part 1** whether a persuasive robot with *more* social cues causes *more* social responses, it also is important to study *which* social cues lead to more social responses. Earlier research by Hancock, Billings, Schaefer, Chen, De Visser, and Parasuranam (2011) has demonstrated that robots' characteristics are instrumental in human-robot interaction. Thus in **Part 2** of the thesis, we aim to test which characteristics of human-like social cues are more persuasive as suggested by Social Agency theory (Mayer et al., 2003) and Social Cues hypothesis (Louwerse et al., 2005). In this part, we investigate two characteristics of human-like social cues implemented on persuasive robots: non-interactive social cues and interactive social cues in the studies presented in **Chapter 6** and **Chapter 7** respectively.

Earlier research demonstrated that non-interactive social cues such as facial characteristics (Deska & Hugenberg, 2017) and similarity in terms of gender between the user and the robot (Akbar, Grover, Mark, & Zhou, 2018; Sandygulova & O'Hare, 2018) can influence social responses. However, these earlier studies did not investigate which non-interactive social cues lead to higher persuasive power (in terms of effectiveness and positive perceptions) as highlighted in overarching research question of this thesis, especially for psychological reactance response. Accordingly in **Chapter 6**, we investigate which non-interactive social cues: facial characteristics of the persuasive robot (trustworthy face: most vs. least) and gender similarity between the users and the robot (similar vs dissimilar) are persuasive. Other than psychological reactance and compliance, we also assess the extent to which the participants believe that the persuasive robot can be trustworthy (for brevity we call this social response as trusting beliefs) in this study.

Research Question 2.1:
What is the influence of facial characteristics and gender similarity used by persuasive robots on the user's psychological reactance, compliance, and trusting beliefs responses?

We expect that participants will experience higher trusting beliefs and higher compliance towards the robot that has the most trustworthy face (than least trustworthy face) and similar gender with the users (than dissimilar gender). However, we cannot predict how non-interactive social cues of robots will affect psychological reactance as earlier research has not yet examined it.

Apart from non-interactive social cues, earlier research of interactive social cues (Kaptein, Markopoulos, de Ruyter, & Aarts, 2011) showed that gesture mimicry (Luo, Ng-Thow-Hing, & Neff, 2013) such as head mimicry (Bailenson & Yee, 2005; Verberne, Ham, & Midden, 2015) and social praise (Fogg, 2002) increased the persuasive power of artificial social agents and perceived positively by humans. Yet, there has been no earlier research on whether robots can use mimicry and social praise in a similar way. Consequently, in **Chapter 7**, we investigate which interactive social cues: head mimicry (absent vs. present) and social praises (absent vs. random timing vs. appropriate timing) are persuasive. Other than trusting beliefs, we also add liking as an extension of social responses measure in this study.

Research Question 2.2:
What is the influence of head mimicry and social praise used by persuasive robots on the user's psychological reactance, compliance, trusting beliefs and liking responses?

We expect that participants will experience higher compliance, higher trusting beliefs and higher liking towards the robot that employs head mimicry and appropriate timing for social praises than the robot with either one or no interactive social cues at all. However, we do not have any expectation on the effect of interactive social cues on psychological reactance due to the scarcity of earlier research in this area.

After identifying whether a persuasive robot with more social cues causes more social responses, and which human-like social cues lead to more social responses, we are able to study the crucial question of whether these social responses cause persuasive robots to be more easily accepted in **Part 3** of the thesis. We examine the roles of social responses: psychological reactance, compliance, trusting beliefs and liking in predicting the acceptance of persuasive robots in **Chapter 8**. We are interested to develop an acceptance model for persuasive robots since it is important to understand users' desire in adopting and using persuasive robots in the future. All social cues that are shown to be effective in the earlier studies (from **Chapter 3** until **Chapter 7**) are implemented in this final study.

Research Question 3:
Do social responses add predictive power to the technology acceptance model of persuasive robots?

We predict that psychological reactance, compliance and trusting beliefs are the key determinants for attitude towards using, while compliance and liking are the key determinants for intentions to use the persuasive robots in the future.

The final chapter presented in this thesis (**Chapter 9)** summarizes all findings by answering the overarching research question and its contributions to the design of persuasive robots through the individual research questions in each chapter. This final chapter also discusses ethical considerations, limitations of the studies described in this thesis, and sketches future research lines in designing persuasive robots.

1.4. Research approach

In this thesis, a laboratory experiments approach (see Webster and Sell (2014)) has been deployed to study users' responses towards persuasive attempts. The laboratory experiments approach has been used widely in social science especially in psychology to establish numerous scientific theories (Thye, 2014). Using standardized procedure, the cause-and-effect relationships between the manipulations of independent variables on dependent variables (causation effect: see (Aristotle, 1985)) are investigated in a controlled environment. Henshel (1980) as well as Webster Jr and Kervin (1971) pointed out that this approach is desirable and beneficial in allowing people to see the world regarding causal relations between the tested variables.

Based on theory-driven methodology (Nunamaker Jr, Chen, & Purdin, 1990), in this thesis we investigate theories related to social cues for the robots and how humans responded to those cues (e.g., Social Agency theory (Mayer et al., 2003)). After deducing the gaps in these theories, we develop several testable hypotheses by identifying the independent and dependent variables that are associated with our overarching research question. Several laboratory experiments are conducted to test the hypotheses. Using IBM Statistical Package for Social Science (SPSS) version 23, the outcomes from the studies are used to confirm (or to refute) those theories to be applied to persuasive robots.

In our studies, a humanoid robot known as Socibot is used as a persuasive agent in all experiments.[1] Socibot is a desktop robot that displays an animated face through back projection and offering some built-in functionalities such as move its head to track the user movements. The controllable face expression and neck tilt ensure realistic and synchronized facial expressions, head posture and voice. The robot is also equipped with lip-synced speech output and can give the impression of maintaining eye contact with the participants throughout the experimental session. Synthetic speech output is played by the robot's speaker in delivering the scripted persuasive messages using English voice.[2] In all studies except the study in Chapter 2, it is given the facial image of a man with light brown skin color tone and hazel eyes.

As suggested in an earlier research (Green, Huttenrauch, & Eklundh, 2004), the robot is operated by an experimenter using Wizard of Oz (WoZ) method (Kelley, 1984) in choosing pre-selected persuasive messages at suitable moments during the interaction with humans. We use WoZ to avoid the need to implement machine perception and AI to enable the robot to react to the actions of the participant. Accordingly, the actions and utterances are pre-programmed by allowing the WoZ to be executed efficiently and in a standardized manner across participants and contexts. We use Natural Language Processing (NLP) requirements to control the robot's verbal cues during the interaction (Fraser & Gilbert, 1991). Some of the requirements in employing WoZ include the possibilities to stimulate the system shortly (given human limitations) and the possibilities to make the simulation convincing.

We use a game as a controllable artificial context for observing choice behaviour of the participants since games are engaging and can keep their concentration high and prevent boredom during the roughly twenty five minutes of the experimental session (Jacobs, 2016; Lawson & Semwal, 2016). Participants are asked to make decisions either to follow or to ignore the persuasive attempts. Importantly, the task in our experiments is artificial (similar concept to an earlier study by Kooijmans and Rauterberg (2007). That is, the participants are required to select the ingredients of a drink in the studies elaborated in Chapter 3, Chapter 4 and Chapter 6. The artificiality of this task helps minimize influences of the participants' own preferences on their decisions. Rather, all found influences on a participant's decisions will be stemming from the prompts of the persuader to cause either the participants to follow or to ignore the advice. We also avoid using contentious and dense topics like politics or religion, societally current debates such as global warming for which very variable levels of involvement and different personal opinions could be expected amongst participants. Also, the theme of the game (e.g.,

[1] https://www.engineeredarts.co.uk/socibot/
[2] http://www.acapela-group.com/

creating a drink) is carefully chosen to ensure that the social responses experienced by participants are solely from the persuasive agent (except for the study in Chapter 4). Whereas in Chapter 7, the participants are asked to select their favorable picture and reward card after being persuaded by the persuasive robot. In Chapter 8, the participants are required to make decisions in selecting the several charity organizations for donation task.

We apply policy of the Department of Industrial Design and the Department of Industrial Engineering & Innovation Sciences for rewarding participants in all studies.

1.5. Key contributions

Although persuasive robots have provided overarching benefits as demonstrated in earlier studies (Ham & Midden, 2014; Looije et al., 2010; Siegel et al., 2009), there are various research problems in need of further investigation. This thesis adds to the current literature by extending our understanding in designing persuasive robots to be accepted based on social responses from users. The contributions of our studies are threefold.

First, the current thesis contributes to scientific knowledge on persuasive technology generally and the contributions to the design of persuasive robots specifically. We argue that it is essential to understand how people perceive diverse social cues of persuasive robots in enhancing the persuasiveness of such artificial social robots and the emerging human-robot interaction experiences. In this thesis, we provide an elaborate account of how the number and the characteristics of social cues for persuasive robots can foster effective and positively perceived persuasive attempts. This account includes the design of non-interactive and interactive social cues for the robots. Therefore, this research assesses the impact of features that represent the state of the art in social robotics: customizing face appearance, interactive social cues, etc.

Second, the current thesis contributes to scientific understanding of human social responses towards persuasive attempts by robots. The earlier research studied to what extent social robots should portray social characteristics to elicit perceived social agency to be able to make use of user's social psychological responses towards the robot (Chetouani, Boucenna, Chaby, Plaza, & Cohen, 2017; Choi, Kornfield, Takayama, & Mutlu, 2017; Thimmesch-Gill, Harder, & Koutstaal, 2017). However, until today, no explicit social cues for persuasive robots are ruled out in order to develop positive interaction with humans. In this thesis, we offer comprehensive studies in understanding psychological reactance, compliance, trusting beliefs and liking experienced by people after being persuaded, in a way that facilitates the use of persuasive robots. With respect to psychological reactance, Ehrenbrink and Prezenski (2017) identified that reactance in human-computer interaction commonly occurs as a result of persuasive attempts. However, the impact of persuasive robots on psychological reactance is understudied, particularly in relation to the impact of implementing different social cues in the robot. This thesis contributes the first investigation of social cues on psychological reactance for persuasive attempts in human-robot interactions.

Third, the current thesis contributes to the body of scientific knowledge on the acceptance model for persuasive robots. Earlier research has claimed that interaction with robots differs from the interaction with other technological artefacts like laptops or smartphones due to the robots' embodiment and the explicitly designed social features in the interaction with humans (Lee, Park, & Song, 2005; Young et al., 2009). This leads to the question of how such social features and social responses to technologies can influence the acceptance of robots as persuasive agents. Bartneck, Nomura, Kanda, Suzuki, and Kennsuke (2005) argued that the biggest challenge in designing social robots is to ensure that people are willing to interact with and accept to use these robots in everyday life. Using the effective and the positively perceived social cues found in earlier studies, we inject psychological realism of social responses into the development of persuasive robots' acceptance model. The model presented helps predict to what extent social responses to persuasive robots determine whether people will use them in daily life.

1.6. Summary

This chapter aspires to develop a theoretical basis and to sharpen the research focus of this thesis in designing social cues for persuasive robots. By exploring existing theories and tracking earlier studies, we have identified research gaps in the current literature and theories.

The remaining chapters in this thesis attempt to bridge this knowledge gap by investigating the social responses on social cues used by persuasive robots in several laboratory experiments. In the next chapter, we present the first laboratory study with humans to investigate their impressions toward social cues displayed by SociBot robot.

CHAPTER 2

Perceive Social Agency of a Social Robot

This chapter is based on a published paper:

Investigating the Effect of Social Cues on Social Agency Judgement (in press). In Proceedings of the *Companion of the 2019ACM/IEEE International Conference on Human-Robot Interaction*. ACM.

In this chapter, we investigate the level of social agency (based on human perception of social cues) embodied in a social robot. We report a comparative evaluation of three sets of verbal and nonverbal social cues (emotional intonation voice, head movement, and facial expression) implemented in the SociBot robot. A convenience sample of eighteen participants interacted with SociBot, in a session where it was used to deliver random facts to them and where they experienced seven sets of combinations of social cues. After each interaction, participants rated the robot's social agency, assessing its representation of a real person and the extent to which they judged it to be like a living creature. As expected, results showed that adding social cues leads to higher social agency judgments; especially facial expression is connected to higher social agency judgments. As a preparatory chapter, results from this chapter will be used in Part 1 of the thesis in determining the level of social agency of the persuasive agents.

2.1 Introduction

Existing research (Li, 2015) recognized the critical role of a social robot to be physically present during the interaction with human. That is, presence of the robots could lead to positive perceivability and higher chances of persuasion compared to telepresent robots and virtual agents. A common approach in enhancing the interaction between humans and robots is by improving the social agency of the robots on to its behaviors and appearances. Studies have pursued this goal for instance by developing an instructive interface of a humanoid robot to act as an actor in theaters (Nishiguchi et al., 2017), endowing a robot with mentalizing stimulus in speech while playing ultimatum game (Nishio, Ogawa, Kanakogi, Itakura, & Ishiguro, 2018), expressing warmth and competence non-verbal behaviours of a robot such as having stable body posture and low pitch for high warmth, high competence condition in delivering lectures (Peters, Broekens, & Neerincx, 2017) besides using emotional expression (Hosseini et al., 2017), enhancing the emotional facial expression, expressivity of words (Delić et al., 2018; Sumi & Nagata, 2013) and bodily movement (Barakova & Lourens, 2010).

An earlier study demonstrated how combinations of verbal and nonverbal cues like sharing information and tool movement on shared screen during robot-assisted surgery can assist surgeons operating remotely (Tiferes et al., 2018). Other than non-humanoid robots, the effectiveness of verbal and nonverbal social cues also has been evaluated in several types of humanoid robots. For example, the Nao robot was used to provide verbal feedback and gesture-based feedback in VR therapy games (Xu, De'Aira, Chen, & Howard, 2018). The Darwin robot was introduced to high school children for tablet-based algebra exam and researchers showed that test scores could be improved by manipulating the robot's verbal and nonverbal social cues (Brown & Howard, 2013).

Earlier literature covered similar comparisons of social cues. Cooney, Dignam, and Brady (2015) showed that extreme head orientation followed by body orientation easily grabbed human social attention. However, little to no attention was given when the head orientation occurred after extreme body orientation. Another study (Fiore et al., 2013) found that robot's proxemics behavior positively affected human perceptions towards non-humanoid robot in terms of the social presence of the robot than the robot's gaze behavior. Nevertheless, we do not know whether the implementations of the social cues on the SociBot will be perceived similarly. To the best of our knowledge, this study is the first to implement some combination of the social cues on this type of device.

Based on the Theoretical Model of Social Influences (Blascovich, 2002b), agency represents the extent to which individuals perceive virtual others as representations of real persons in real time. For our study, a SociBot robot was programmed to present human-like facial, bodily and voice tone expressions while conveying information to the participants. This study aims to evaluate these social cues implemented in this robot. Specifically we assessed the influence of these cues on people's assessment of this robot's social agency. Based on the definition of social agency, we asked the participants to rank the robot with several combinations of social cues through their judgment of the robot's representation of a real person, and the extent to which they judged it to be like a living creature. We expected that this evaluation would enable controlling the level of verbal and non-verbal cues in the context of thought change applications for the following studies.

2.2 Materials and Methods

2.2.1 Participants

Eighteen participants aged 25 to 39 (10 males, 8 females; age M = 29.89, SD = 3.48) were recruited amongst graduate students in the Industrial Design department from Eindhoven University of Technology for a 30-minute study.

2.2.2 Manipulation

The characters for social robot in this study were implemented on the SociBot. The first character appeared on the robot's face called Mat. A neutral character called Oliver, a default character with natural expression and blinking eyes appeared in all sessions. Additionally, seven target characters with different names that showed various sets of social cues were presented in each session (the experimental manipulation; see Figure 2.1). Mat was designed with a 3D-printed face as a Spiderman, differently than other characters (including Oliver) with a humanoid face since Mat was used as a moderator throughout the experiment while the others was used as target characters.

In seven sessions, the manipulation of verbal and nonverbal cues of the respective social robot were varied as follows:

1. Emotional intonation voice (William)
2. Facial expression (Harry)
3. Head movement (Charlie)
4. Emotional intonation voice and facial expression (James)
5. Emotional intonation voice and head movement (Thomas)
6. Facial expression and head movement (Daniel)
7. Emotional intonation voice, facial expression and head movement (Ethan)

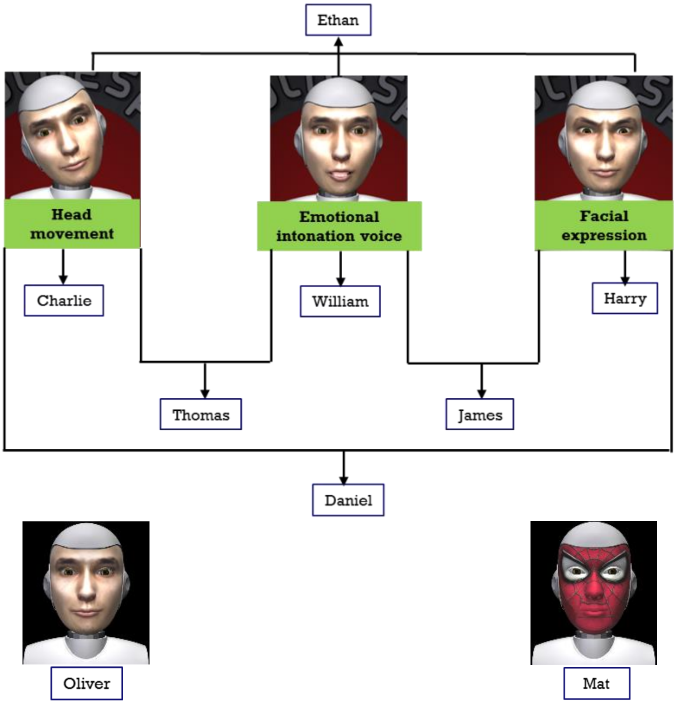


Figure 2.1: Manipulations of number and type of social cues.

2.2.3 Task

The experimental was set up in a dedicated room (see Figure 2.2). Participants arrived at the room on scheduled times, read and signed the consent form, and were asked about their familiarity of the experimental setup. Then, the session was taken over by the robot in the guise of a character called Mat (the moderator). After answering questions on demographic information, the series of interaction sessions with the neutral and seven target characters started.

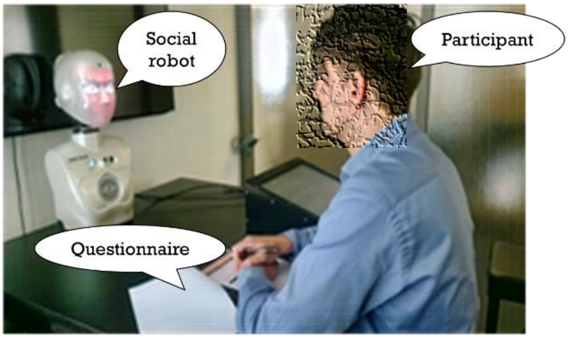


Figure 2.2: Experimental sets up.

Two characters appeared in each session (Oliver and one target character). Both characters would recite the same random fact; with the target character using its set of social cues. Next, the participant started the consequent session by touching a screen placed near to them as demonstrated by an experimenter earlier. After the seventh session, the moderator thanked the participant and asked him/her to fill out a paper questionnaire. Participants could replay particular sessions (showing a character and its social cues), to help them remember the characters.

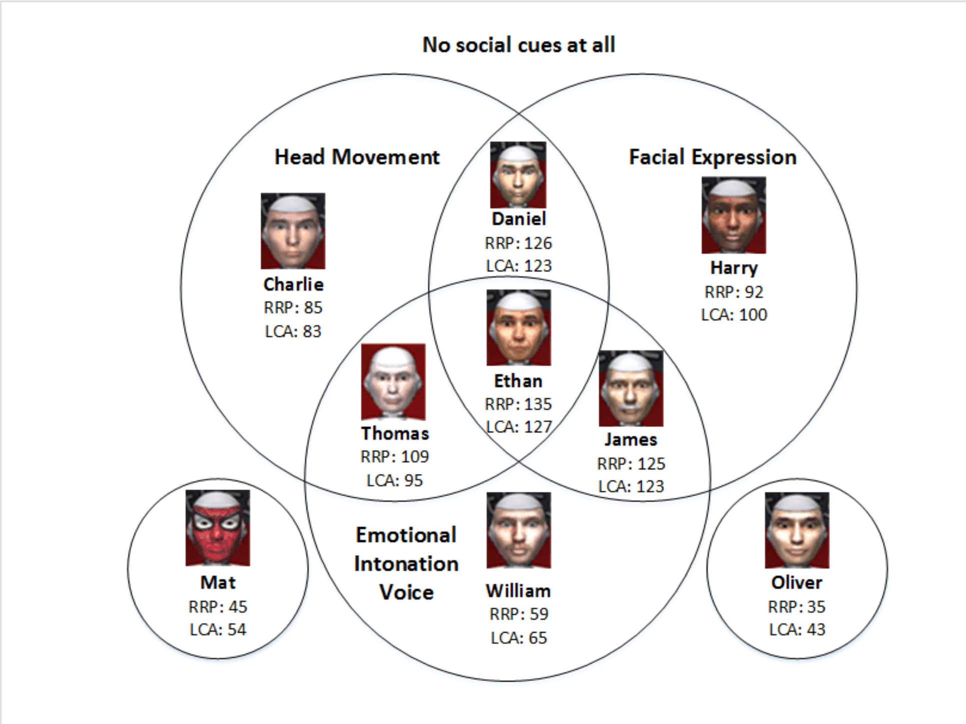
2.2.4 Measures

To measure their social agency judgment of each robot character, participants were asked to rank all characters (including the moderator, Mat and the default character, Oliver) on a scale indicating 'the most real' (1 = unreal to 9 = very real) and a scale indicating 'like a living creature' (1 = unlike to 9 = very like). Finally, participants were requested to provide comments or suggestions for improving the experiment. A reliability test resulted in a satisfactory Cronbach's $\alpha = 0.82$.

2.3 Findings

Agency refers to the extent in which people perceive (virtual) agents as representations of real persons in real time (Blascovich, 2002b). Figure 2.3 shows participants' social agency judgments for all characters (its representation of a real person, and the extent to which they judged it to be like a living creature).

As suggested by the Social Agency theory (Mayer et al., 2003), we found that characters with stronger (or more) social cues lead to more social interaction by receiving higher social agency scores than the characters with less social cues. That is, results showed that participants evaluated the characters that have more social cues to have a higher Representation of Real Person (RRP) score (e.g., Ethan, $M = 7.44$, $SD = 2.18$) than the characters that have less social cues (e.g., Charlie, $M = 4.72$, $SD = 1.45$) and no social cues (e.g., Mat, $M = 2.50$, $SD = 2.33$), indicated by a Friedman test $\chi^2(8) = 80.43$, $p < 0.001$. Similarly, the participants evaluated the characters that have more social cues to have a higher Living Creature Alike (LCA) score (e.g., Ethan, $M = 7.06$, $SD = 2.39$) than the characters that have less social cues (e.g., James, $M = 6.83$, $SD = 1.69$) and no social cues (e.g., Oliver, $M = 2.39$, $SD = 1.54$), indicated by a Friedman test $\chi^2(8) = 58.53$, $p < 0.001$. That is, the participants scored the characters that have stronger (or more) social cues with higher social agency scores than the characters with less social cues. That is, results showed that Oliver (the default character with minimal or no social cues) scored the lowest marks of RRP and LCA, followed by Mat (the moderator with minimal or no social cues), William and Charlie (characters with at least one social cue). Accordingly, James and Daniel (characters with at least two social cues) were ranked as the neutral-real and neutral-living creature alike characters. Ethan (a character with the combination of three social cues) scored the highest marks as the most real (RRP) and the most like a living creature (LCA).



Notes: 1. Representation of real person (RRP)
2. Living creature alike (LCA)
3. Scores of RRP and LCA = Σ (Rank x Number of votes)

Figure 2.3: The social cue types (head movement, facial expression, and emotional intonation voice), their combinations, and the social agency scores (by users) for each of the robot characters using a combination.

2.4 Discussion

There are two remarkable findings that should be highlighted from this first study. Firstly, the characters' roles are quite influential in the rating of the characters. The participants tended to choose Mat (the moderator) over Oliver (the neutral character) although both of them were in the default condition since Mat was claimed as 'wise' as a real human in conducting the session while Oliver just 'boldly' appeared in each session.

Secondly, facial expression appears to be the most powerful social cue that has a major impact upon the perceived anthropomorphism of a social agent. When facial expression was included, the participant's scores for real person representation and living creature likeness were highest. It can be observed from both sessions of one social cue only and the combination of two social cues which Harry and Daniel scored the highest marks in both items compared to the other characters in the same category.

In the comments or suggestions column, it was mentioned most participants mentioned that there was some noise originating from the social agent's body that caused them to feel uncomfortable and distracted during the experiment. The noise sound then became more obvious during the sessions that included certain head movement. As consequence, their concentration level during the experiment was affected by this factor.

2.5 Summary

This chapter aimed to investigate social agency level of a humanoid robot based on several combinations of social cues: emotional intonation voice, head movement, and facial expression. We found that facial expression was the most powerful social cue for a social robot, and combining all three social cues results in the highest perceived social agency. Throughout this thesis, we equate the social agency with the richness of social cues based on the findings in this chapter. That is, we found that the more social cues added to the social agent, the more people perceived the agent as the representations of real person eventhough the agent was controlled by the same human-being. Thus, based on the definition by Blascovich (2002b), we claim that the higher number of social cues implemented on the robots, the higher the social agency of the robots. Head movement should be used sparingly as the noise from the motor diminished their effectiveness as social cues. These findings increase our understanding of robot social cues and perceptions of its (artificial) social agency.

Going forwards, we use SociBot as a persuasive agent with different combinations of social cues to represent two social agency conditions. Based on the results from this study, we use the combination of social cues: emotional intonation voice, head movement and facial expression on a robot as the highest social agency condition in the next studies.

PART I
NUMBER OF SOCIAL CUES

In this part, we investigate the influence of the number of social cues for persuasive agents on social responses. Presented earlier in Chapter 2, we conducted a preliminary study to investigate humans' perception of social agency of a robot in displaying different sets of social cues. Presented in Chapter 3 and Chapter 4, we conducted two studies to investigate the influence of the number of social cues represented by a persuasive robot (either with minimal cues or with enhanced cues) on psychological reactance and compliance. As a baseline, we used advisory-text as a persuasive agent in comparing the same effects. Other than the number of social cues, Chapter 3 and Chapter 4 investigated social responses through coerciveness of the language used by the persuasive agents and psychological involvement in decision-making tasks separately. In Chapter 5, we conclude Part 1 of the thesis by combining the data points from Chapter 3 and Chapter 4 that has the same hypothesis to explore the desirable number of social cues for persuasive robots so that the persuasive attempts will be effective (high compliance) and positively perceived (low psychological reactance) by humans.

CHAPTER 3

Pardon the Rude Robot: Social Cues Diminish Reactance to Highly Coercive Language

This chapter is based on published papers:

Pardon the rude robot: Social cues diminish reactance to high controlling language (2017, August). Paper presented at *26th IEEE International Symposium on Robot and Human Interactive Communication* (pp. 411-417). IEEE. DOI: 10.1109/ROMAN.2017.8172335

The Influence of Social Cues and Controlling Language on Agent's Expertise, Sociability, and Trustworthiness (2017, March). In *Proceedings of the Companion of the 2017ACM/IEEE International Conference on Human-Robot Interaction* (pp. 125-126). DOI: 10.1145/3029798.3038410

In the previous chapter, we unveiled the social agency judgement on different combination of social cues displayed by SociBot in delivering random facts. Importantly, we found that the more social cues displayed by an artificial social agent, the higher the representation of that agent to a real person resulting the higher social agency of that agent. However, in many future social interactions between robots and humans, robots may need to convince people to change their attitudes, behaviors, or thoughts. People may dislike and resist such persuasive attempts, a phenomenon known as psychological reactance. By using SociBot as a persuasive agent, this chapter examines how psychological reactance, measured in terms of negative cognitions and feelings of anger, is affected by the persuading agent's social agency cues and coerciveness of language used. Participants played a decision-making game in which a persuasive agent attempted to influence their choices exhibiting highly or slightly coercive language, and three different levels of social agency. This chapter suggested that slightly coercive language leads to the increment of reactance when the persuasive agent does not exhibit social cues. Surprisingly, reactance is not affected by coerciveness of language in the same way when the persuading agent is a social robot exhibiting social cues.

3.1 Introduction

A persuasive attempt can often lead to the opposite responses and behaviors than desired. Parents advising their teenaged children is a recognizable example of such a situation. Consider for example a mother attempting to convince her 11 year old daughter to put a warm coat on before going out in the cold. This girl might react negatively not because she really minds doing so or because she does not think this is a sensible thing to do, but because she perceives her mother's suggestion as a threat to her autonomy in making her own decision as a grown-up. She might then exhibit erratic behaviors like putting an angry face, ignoring her mother, or making a point of going out in the cold weather lightly dressed.

While puberty is an extreme and stereotyped demographic, this reaction is not uncommon when people are confronted with a strong persuasive attempt. This phenomenon is known as *psychological reactance*. Psychological reactance in a persuasion activity is triggered when the persuadee senses his or her freedom in making a decision is eliminated, threatened, or limited by the persuader (Brehm, 1966). The persuadee may ignore the persuader, or resist the persuasive attempts by doing the opposite of what they request to do (Brehm, 1966; Brehm, 1972). Psychological reactance also can lead to irregular behaviors in restoring freedom to make a decision. It can also be manifested in physical expressions such as showing a dissatisfied face and through emotional communication such as shouting (Quick and Considine, 2008). Even in cases of complying with the persuader, reactance may be manifested as feelings of anger and negative thoughts (Dillard & Shen, 2005). Earlier research (Dillard & Shen, 2005; Lee, Lee, & Hwang, 2014; Rains & Turner, 2007) has shown that psychological reactance can be measured using questionnaires.

Several experimental studies have attempted to identify the cause of psychological reactance and how people behave to portray their reaction towards the reactance. For example, an earlier research has shown that forceful language in persuasive communications in a health campaign can be a source of reactance (Quick & Considine, 2008). Other studies of reactance suggested that lexical concreteness (Miller, Lane, Deatrick, Young, & Potts, 2007), persuasive attempts (Laschke, Diefenbach, Schneider, & Hassenzahl, 2014; Roubroeks et al., 2011), privacy violations (Lee & Lee, 2009) and regulatory policies (Song, McComas, & Schuler, 2018) are the examples of factors influencing the level of psychological reactance (Ehrenbrink & Prezenski, 2017).

Earlier studies showed that the coerciveness of language used in conveying persuasive messages affects the persuadee responses toward the advocated behaviours (Burgoon, Alvaro, Grandpre, & Voulodakis, 2002; Miller et al., 2007; O'Keefe & Klumpp, 1997) but provided mixed results (Buller, Borland, & Burgoon, 1998; Dillard & Shen, 2005; Grandpre, Alvaro, Burgoon, Miller, & Hall, 2003; Miller et al., 2007; Quick & Stephenson, 2007a; Rains & Turner, 2007). It has been argued that the coerciveness of language used in conveying the persuasive messages could also provoke psychological reactance to occur (Grandpre et al., 2003; Miller et al., 2007). Miller et al. (2007) argued that coerciveness of the language used in delivering a persuasive message plays an important role, in which dogmatic or highly coercive language might trigger reactance, whereas a slightly coercive message might be more effective. An earlier study carried out by Quick and Stephenson (2008) showed that highly coercive language was perceived as threatening by the users. Examples of highly coercive language include imperative words like '*must*', criticism towards other viewpoint such as '*A rational human being would unquestionably agree that*….' supreme affirmation and threatening warning for example '*You cannot deny this idea!*' On the other hand, the less derisive and imperative languages such as '*Can you please*…', as well as qualified proposition like for example '*I think it is better to*…', were less dogmatic and would inflame less reactance (Bushman, 1998).

An earlier research of reactance in interactions between humans and artificial social agents suggested that social agency of the messenger can trigger higher psychological reactance. Specifically, Roubroeks et al. (2011) reported an online experiment where the level of social cues provided was manipulated: text-only without any social cues, text accompanied by a still picture of a robotic agent called iCat, or text accompanied by a short video-clip of the same robotic agent. Also, the experimenter manipulated coerciveness of language of the agent which could be either highly coercive (e.g., '*you have to*…') or slightly coercive (e.g., '*you may*…'). The target behaviour pertained to choosing environmentally friendly settings for a washing machine on a simulated task; choice behaviour was assessed by a question regarding preferred settings after receiving advice from the agent. Confirming reactance research, highly coercive language led to more reactant responses. In this study, participants experienced more psychological reactance when the agent displayed more social cues (text accompanied by the short film clip) or some social cues (text accompanied by still picture), than when the agent had very limited social cues (text-only). Based on this finding, it was concluded that stronger social agency of the messenger can lead to higher psychological reactance (Roubroeks et al., 2011).

However, we note that the level of social agency achieved in the experiment by Roubroeks et al. (2011) was rather low compared to the capabilities of social robots, as the agent was not truly interactive and participants were confronted with images of the robot rather than the robot itself. In order to develop a solid understanding of psychological reactance towards social robots, it seems necessary to replicate these results with an experiment exposing users to actual social robots in the role of the persuader. Moreover, such an experiment appears necessary as the expectation that social cues will enhance reactance is equivocal. It could also be that higher social agency will mitigate reactive responses in the same way that higher social presence in interpersonal communication can temper negative emotions. Based on the Media Equation hypothesis (Reeves & Nass, 1996), we argued that when participants perceive technology to have clear social agency, their responses to the technology will become inherently social. Thereby, a persuasive agent that is perceived to be a social agent may cause reactance, but at the same time, it may be ascribed social characteristics, e.g., being an authority and knowledgeable on the topic at hand, which could make the advice more palatable to the user thus preventing reactance responses. At the same time technological persuaders that are not perceived as social agents may trigger reactance but will not activate such social source characteristics.

The Current Study

In this study, we investigated the influence of persuader social agency level on reactance elicitation in an experiment that involves a stronger manipulation of social agency levels than the purely on-screen materials used in an earlier research (Roubroeks et al., 2011), aiming to enhance the external validity of the results for the human-robot interaction research field. At the higher end of social agency, persuasive messages were delivered by the SociBot. This study compared the psychological reactance caused when highly coercive language was used by a persuasive agent with high social agency (the SociBot displaying several social cues) or medium social agency (the SociBot displaying minimal social cues) or a non-social agent (a computer display presenting the same information textually). These agents advised the user towards a choice behaviour (described in Section 3.2.3) by using either highly or slightly coercive language. Psychological reaction was assessed by the observed compliance to the given advice and by self-report measures to assess feelings of anger and negative cognitions of the users. We expected that:

- H1. There is a significant difference in psychological reactance score between participants who received the advice expressed in highly coercive language and those who received advice expressed in slightly coercive language.
- H2. An interaction between the persuader social agency level and the language used towards psychological reactance.
- H3. There is a significant difference in psychological reactance score between participants who received advice from an agent with higher levels of social cues (the social agent displaying more social cues) and those who received advice from an agent with lower levels of social cues (the social agents displaying less social cues)

3.2 Materials and Methods

3.2.1 Participants and Design

Sixty participants were recruited at Eindhoven University of Technology aged 20 to 55 years old (29 males, 31 females; age M = 28.68, SD = 7.57). Participants were randomly assigned to one condition of a 3 (social agency: high vs. medium vs. low) by 2 (coerciveness of language: high vs. slight) between-subjects experimental design. A between-subjects experimental design was used in this study to avoid the carry-over effects as found in within-subjects design study (Yang et al., 2017). For a participation lasting approximately thirty minutes, participants received a gift voucher worth €10 as a token of appreciation.

3.2.2 Manipulations

Manipulation of Social Agency

Three levels of social agency were employed in the study: high, medium and low (for an overview, see Figure 3.1). A computer display presenting the advisory text was used in all conditions. In the high social agency (HSA) condition, a SociBot was positioned next to the computer display. The Socibot expressed verbal and nonverbal cues through the movement of its head, eyes and mouth. These social cues were presented when the robot was giving advice during the game appended with an audible sound. In the medium social agency (MSA), the SociBot was used in precisely the same way, but now without verbal and nonverbal cues (except for a neutral facial expression and blinking eyes) as shown in Figure 3.1. In the low social agency (LSA) condition, the robot was not present, and the agent delivering the advice was only the computer display. The experimental setup is illustrated in Figure 3.2.

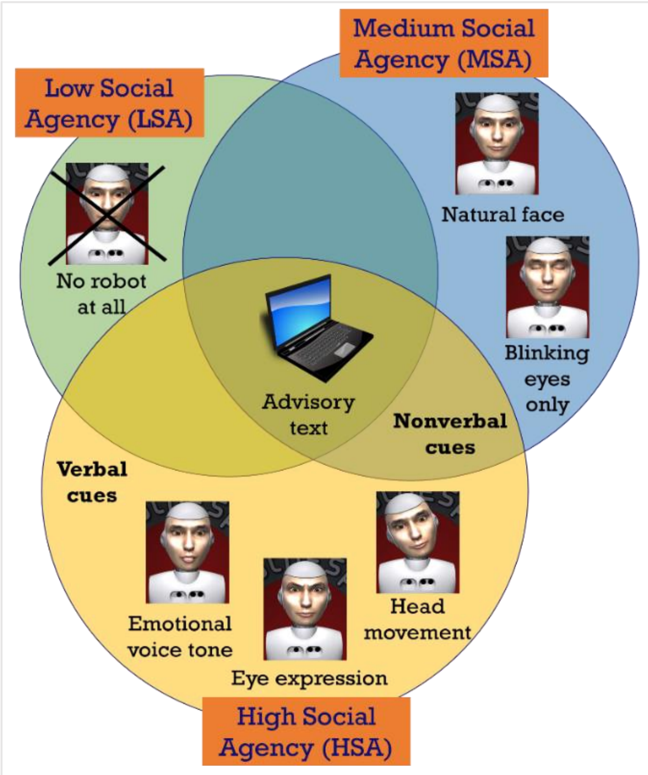


Figure 3.1: Manipulation of social agency conditions.

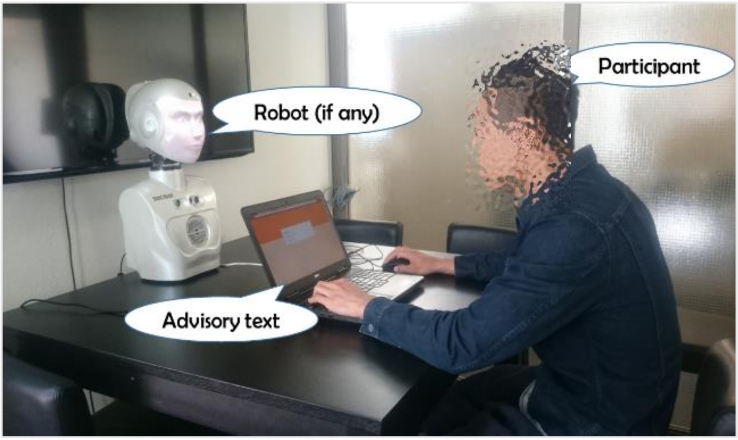


Figure 3.2: Experimental sets up.

Manipulation of Language's Coerciveness

We presented the same advice to participants using two different kinds of wording in this study. Highly coercive language used explicit or direct verbs (e.g., *'You must '…, 'You have to…'*). Slightly coercive language used less imperative and less derisive language in conveying the advice (e.g., *'Would you mind...?', 'You may want to...'*).

3.2.3 Task

The game-like task used in this experiment was inspired by an online game called 'Smoothie Maker: Creation Station'.[1] In the original online game, the participants make several decisions, e.g., regarding which fruit they prefer or which straw they find attractive to use for drinking the smoothie. Based on this theme, we used Matlab software to create a game called 'Beverages Creation Station' to use in our studies, including the studies presented in the next chapters, (refer to Figure 3.3 for the game interface). In adapting the original game concept for this experiment, several changes have been made. First, the role of the social agent was to advise the participants after each smoothie selection had been created. Second, the choices given in each task were different from the original game to fit the participants' age range and to ensure the anonymity of choices. Third, the level of psychological involvement towards the game was changed from high involvement to low involvement. Instead of creating one's own drink as in the original game, participants were asked to create a drink for an alien. Thereby, in this task there will be no influences of a participant's earlier knowledge or preferences on participant's decisions. Rather, all influences on a participant's decisions found will be stemming from the agent: either a participant follows advice, does not use it, or shows evidence of reactance in his/her behavior. Also, the game consisted of multiple tasks to give the opportunity for repeated interactions between the participants and the social agent. Ten tasks needed to be completed by the participants in each session. The background sound from the original game also was removed to avoid distracting participants during the experiment.

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[1] https://www.youtube.com/watch?v=kpOkF_7_epc


(a)
Beverages Creation Station
START
THIS IS THE REAL GAME.
The rules for the real game are as same as the demonstrated version.
In this game, you have to make several selections based on your own choice. Then, the advisor assigned will advise you accordingly.
You are free to make decision either to
1. Stick with your earlier decision
OR
2. Follow the advice given
BEAR IN MIND!
There are no right or wrong answers in this game.
CHOOSE WHATEVER YOU WANT!
LET'S START!
This is a science fiction game in creating marvellous drink for aliens.
You have only ONE chance to create a FREE drink and PROUDLY serve it to the alien over the galaxy.
Let's join our crew and help us with the drink creation by clicking 'NEXT' button.
Please remember!
The drink is for the ALIEN, not for you.
NEXT
CLOSE
Reminder for the game's involvement level
(b)
Initial choice
Welcome ☺
Task 1:
It's time to choose which drinks you prefer to serve to the lovely alien.
Initial Choice
Final Choice
Please press ENTER (at the keyboard) after each selection. Thanks =)
① Smoothie
② Juice
③ Shake
(c)
Advice 1
What a bad choice. The structure of the drink you chose before was very bad for the alien health condition. You must serve other drink to the alien. I am sure it will love it!
OK
Advisory-text
(d)
Advice 1
Advisor saying...
OK

(e)

(f)

(g)

Figure 3.3: Graphical User Interface (GUI) of the game:
(a) Introduction and rules of the game (b) Example of the task and the initial choice box (c) Advisory-text window (for low social agency)
(d) Notification window (for medium and high social agencies). Robot started conveying the advice audibly parallel with the notification window
(e) Final choice box (f) Instruction for proceeding to the next task and NEXT button (g) End-of-game notification and CLOSE button.

3.2.4 Procedure

Participants were escorted to a designated room, read some instructions about the study and provided informed consent and demographic information. Then, the experimenter would check whether the participants were somehow already familiar with the experimental setup or the experimental hypotheses and introduced them to the agent according to the experimental condition to which the participant was assigned. Just as the advisory text on the computer display, the social agent was introduced as an advisor, and not as a mentor or a persuader to present the robot as someone of equal social power with the participants.

Interaction between the agent and a participant was one-way: the social agent communicates advice but would not react to participants' enquiries. Before the session started, the experimenter explained the rules regarding the experimental task mentioning that there were no correct answers. The rules were also repeated in text (on the computer display) before the participants started the experimental task, to make sure they really aware that they are free to choose exactly what they think and feel right, and that there was totally no compulsion to change their choice based on advice by the advisory agent (computer display or robot). After that, the participant was acquainted with a GUI of a game-like experimental task presented on a laptop computer. If the specific experimental condition involved SociBot, the robot was placed facing the participant behind the laptop as shown in Figure 3.2.

The experimenter first demonstrated how to play the game using the 'Demonstration' GUI. The 'Demonstration' GUI was the same as used during the session. The experimenter would leave the room after the participants had no more questions about it and the social agent would take over for the remainder of the session.

During the game, the participant had to complete ten tasks, and each task consisted of a multiple-choice question (with two, four or ten options). For each task, the participant had to make their own choice and then indicate their choice in the 'Initial Choice' box on his/her answer sheet. The participant was asked to make their initial choice based on what 'first popped up in their mind' for each question. Whatever choice participants would make, the advisor would not agree and would try to persuade them to change it. The social agent would deliver an advisory message intended to persuade the participant to change his/ her initial choice using slightly or highly coercive language (dependent on condition). The participants were also reminded that the social agent has a similar level of social power with the participants in making a decision. Specifically, participants were told that *'You are free either to follow or to ignore the advice given. There will be no right and wrong answers in this game'*.

The participant could then choose between two responses to the message above: keep their initial selection of the container size (ignore the advice), or change their mind and select a container with a different size in following the advice by filling in the 'Final Choice' box. After the end of each task, the next of the ten tasks started, in which another decision about a drink ingredient had to be made. At the end of the session, the participant requested to fill in a questionnaire in which their feeling of anger and negative cognitions towards the agent were measured in Google form. Finally, a voucher was presented by the experimenter before the participant was debriefed and dismissed.

3.2.5 Measures

A questionnaire was utilized to assess the reactance experienced by the participants in each condition. The questionnaire consisted in three main sections: the degree of threat towards the participants' autonomy when the advice was given, the attitudes of the participants towards the advice and the feeling after being advised. A 5-Point Likert scale was used to assess attitudes ranging from (1) completely disagree, (3) neutral to (5) completely agree. No time limit was set for filling out the questionnaire. The questionnaire elements are described below.

Perceived Threat to Autonomy

Walter and Lopez (2008) defined perceived threat to autonomy as the degree to which a person believes the threat could control the condition or content of his/her autonomy in making a choice. Since a persuasive attempt may be associated with autonomy in decision making, we wanted to check whether the participants were likely to perceive the persuasive attempts by different level of social agency as different levels of threat to their autonomy. The perceived threat to autonomy measure consisted of four statements which were: *'The advisor restricted my autonomy to choose what I want to serve', 'The advisor tried to manipulate me', 'The advisor tried to make a decision for me'* and *'The advisor tried to pressure me'.* Participants could answer on a 5-point Likert Scale ranging from (1) completely disagree to (5) completely agree.

Psychological Reactance

The participants' reactance levels were expressed in both 'Feelings of Anger' and 'Negative Cognitions'. They could rate the extent to which they felt irritated, angry, annoyed as well as aggravated using a Likert scale in the questionnaire (Dillard, Kinney, & Cruz, 1996; Dillard & Peck, 2000) and were invited to freely voice out their cognitions by writing as much words as they like after completing the experiment in 'Cognitions' section. At the end of the 'Cognitions' section, participants were asked to label the words or sentences they wrote as positive (P), neutral (Neu) or negative (N) (Dillard & Shen, 2005; Quick & Stephenson, 2007b). Then the negative cognitions were counted using the cognition scale developed by Shaver, Schwartz, Kirson, and O'connor (1987) and according to the procedure proposed by Dillard and Shen (2005). After that, the negative cognitions score was submitted as one of the components in psychological reactance measure in percentage form (Roubroeks, Midden, & Ham, 2011).

Response to Advice and Recommendations

To represent the reaction level of the participants towards the advice and recommendations given, the Measurement of Psychological Reactance produced by Donnell, Thomas, and Buboltz Jr (2001) was replicated in this study.

Compliance

The compliance of participants was measured as the number of times participants changed their initial decision to comply to the agent's advice. Participants had ten choice moments during the experimental session. In case the initial choice was the same as the final choice, then the participants would not get any compliance point for that particular task. In contrast, if the initial and final choices were inconsistent, it showed that the participants were successfully being persuaded by the advisor to change their choice and they would be awarded 1-point for that particular task. E.g., if a particular participant would follow social agent's advice and changed his/her final choice as instructed for task number 2, 3, 4, 5, 8 and 10 and was incompliant for the other four tasks; then he/she would be given the compliance score of 6.

3.3 Findings

3.3.1 Manipulation Check

Results showed that our manipulation of highly (vs slightly) coercive language use was successful. That is, participants reported higher perceived threat to autonomy in the highly coercive language condition (M = 3.56, SD = 0.96, n = 30) than the slightly coercive language condition (M = 3.04, SD = 0.87, n = 30) with $F(1,58) = 4.65$, $p < 0.05$. In line with earlier research (Roubroeks et al., 2011), our social agency manipulation did not have a main effect on a participant's perceived threat to autonomy.

As described earlier in the introduction section on the definition of psychological reactance, the hypothesis constructed in this study was based on the psychological reactance score which consists in both feelings of anger and negative cognitions scores. While the feelings of anger score is calculated from the Likert Scale questions, the negative cognitions are computed based on the percentage number of negative words reported during the experiment. As result, only a weak correlation was found between feeling of anger and negative cognitions ($r = 0.14$), *n.s.* This finding associated with the conclusion made by Dillard and Shen (2005) that these two variables are separate constructs but related in measuring psychological reactance.

3.3.2 Hypothesis Testing

Hypothesis 1: Psychological Reactance

To evaluate the first hypothesis, the psychological reactance scores (negative cognitions and anger scores) was submitted to a 2 (coerciveness of language: high vs slight) x 2 (reactance score: negative cognitions vs anger score) repeated measures Analysis of Covariance (ANCOVA) as demonstrated in earlier study (Roubroeks et al., 2011). 'Response to Advice and Recommendations' (RAR) score also was used as a covariate in measuring participants' tendency of reactance towards advice and recommendations (see Donnell et al. (2001)). Confirming hypothesis 1, this analysis showed a significant main effect of coerciveness of language on reactance, $F(2,56) = 3.19$, $p < 0.05$, partial $\eta^2 = 0.10$.

We employed two separate ANCOVAs to investigate the influence of coerciveness of language on the components of reactance: feelings of anger (the first ANCOVA) and negative cognitions (the second ANCOVA). Results showed that the effect of coerciveness of language was only significant for feelings of anger, $F(1,57) = 6.43$, $p = 0.01$, but not for negative cognitions, $F(1,57) = 0.00$, $p = 0.95$.Table 3.1 shows the mean scores and standard deviations for negative cognitions and feeling of anger (and standard deviations between brackets) in the different experimental conditions.

Table 3.1: Mean scores on psychological reactance elements (and standard deviations between brackets) for the coerciveness of language manipulation.

Psychological Reactance	**Coerciveness of Language**	
	Slight	***High***
Negative Cognitions	17.33(20.16)	15.33 (22.09)
Feeling of Anger	2.21 (0.88)	2.58 (1.03)

Thereby, these results suggested that participants experienced higher level of anger in highly coercive language condition than in the slightly coercive language condition, but present no evidence that negative cognitions after an interaction with an agent using highly coercive language were different from after interaction with an agent using slightly coercive language.

More importantly, the second hypothesis (H2) predicted a significant interaction between social agency and coerciveness of language with psychological reactance. To test this hypothesis, the psychological reactance score (negative cognitions and anger score) was submitted to a 2 coerciveness of language (HCL vs. LCL) x 3 social agency (LSA vs. MSA vs. HSA) x 1 (RAR as a covariate) ANCOVA test (this test was selected based on earlier research by Roubroeks et al. (2009). Repeated measure analysis was conducted to evaluate the hypothesis. The results indicated a significant interaction effect of social agency and coerciveness of language manipulations on psychological reactance, $F(2,53) = 3.22$, $p = 0.05$, partial $\eta^2 = 0.11$. Further explorations of the relationship between the dependent and independent variables in verifying the third hypothesis are elaborated in Table 3.2.

Table 3.2: Mean scores on psychological reactance for the levels of coerciveness of language and social agency manipulations.

Coerciveness of Language	**Social Agency**		
	Low	***Medium***	***High***
Slight	4.37 (10.61)	10.46 (10.54)	12.99 (10.74)
High	13.91 (10.56)	5.53 (10.50)	8.93 (10.56)

Two conclusions can be drawn in line with the third hypothesis (H3). First, that when participants interacted with an agent without social cues, highly coercive language caused higher reactance. However, when participants interacted with an agent that displayed some social cues (a medium or high level of social agent), highly coercive language led to a decrement of participant's reactance. Second, in the slightly coercive language case only, the psychological reactance increased along with the level of social agency.

Figures 3.4 illustrates the effect on psychological reactance (feeling of anger and negative cognitions) resulting from the manipulation of social agency and coerciveness of language. In the low social agency condition, higher coerciveness of language resulted in more psychological reactance reported but the opposite trend was observed with the medium and high social agency conditions.

Furthermore, results did not support the view that higher social agency led to more psychological reactance: a similar ANCOVA that used to test H1 with social agency as an independent variable (instead of coerciveness of language as for H1) presented no significant effect of social agency manipulation on psychological reactance $F(2,56) = 0.39$, $p = 0.68$. Two separate ANCOVAs were employed to investigate the influence of social agency on the components of reactance: feelings of anger (the first ANCOVA) and negative cognitions (the second ANCOVA). Results showed no significant influence of social agency on both components of psychological reactance; feelings of anger: $F(2,56) = 0.26$, $p = 0.77$ and negative cognitions: $F(2,56) = 0.40$, $p = 0.67$.

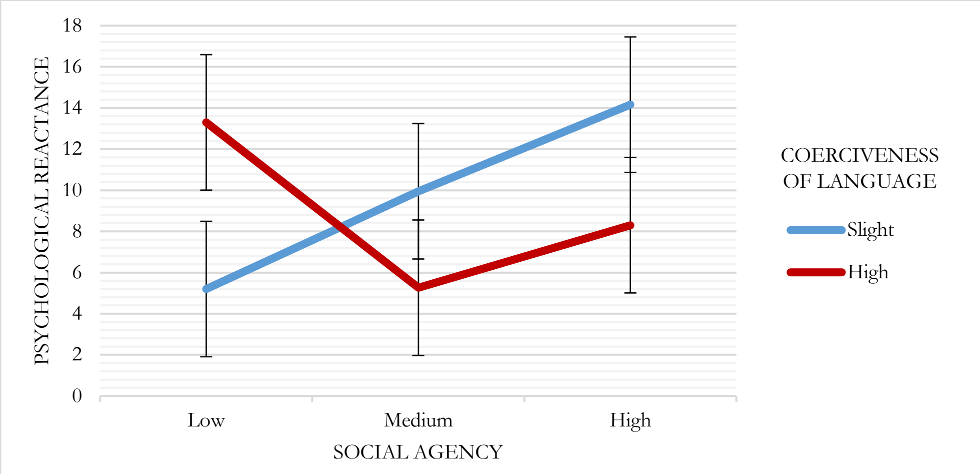


Figure 3.4: Mean and standard error of psychological reactance scores by social agency (low vs. medium vs. high) and coerciveness of language (slight vs. high).

Hypothesis 2: Compliance

Compliance was also measured in this thesis by the number of participants who changed their answer after receiving the agent's advice (labelled as compliance as shown in Figure 3.5). Two separate Multivariate Analysis of Covariance (MANCOVA) were carried out to investigate the degree of compliance based on the manipulations of social agency and coerciveness of language. Results showed that there was no significant main effect of social agency on compliance, $F(20,96) = 0.81$, $p = 0.69$ but there was a significant relationship on coerciveness of language to the compliance, $F(10,48) = 2.98$, $p = 0.01$. A close examination showed that the number of participants who followed the advice to change their answer was higher when highly coercive language was used than when slightly coercive language was used, independent of which social agent delivered the advice. For slightly coercive language, the total compliance recorded was 97 while 170 for highly coercive language.

Regarding the tasks order, as demonstrated in Figure 3.5, in the slightly coercive language condition participants started the task by following the agent's advice but after some time (starting from task 4) they began to ignore it. Meanwhile in highly coercive language case, most of the time the participants would follow the advice that had been delivered by the designated social agent.

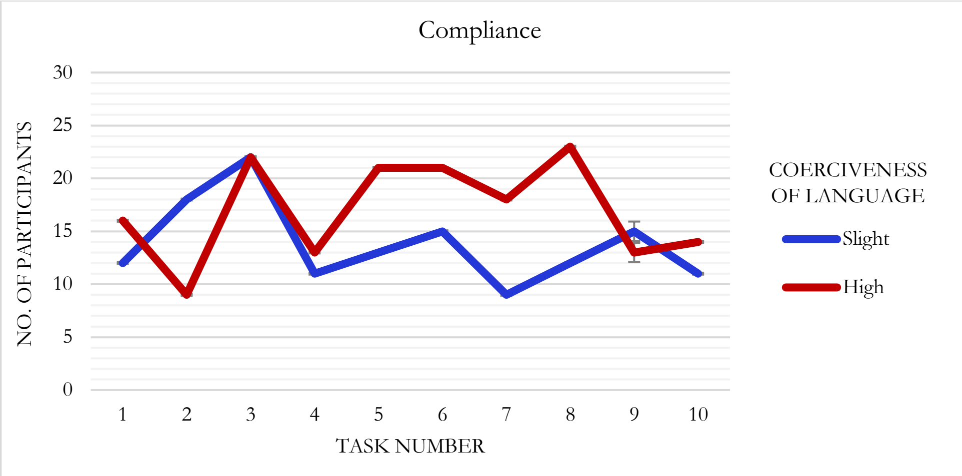


Figure 3.5: Mean and standard error of compliance scores by coerciveness of language (slight vs. high).

3.4 Discussion

This chapter investigated how psychological reactance experienced by participants was affected by social agency and coerciveness of language manipulations. In this study, the content of the decision task was inspired by earlier research (Roubroeks, Ham, & Midden, 2010) but differs in two ways. First, we assessed actual interaction between a human and a robot and not an online interaction with an artificial agent. Second, the context of the game's goal "serving the most delicious drink to the aliens" was different from the study of Roubroeks et al. (2010). Other studies tested whether dominance and extroversion in the robot language will peruse participants to follow the robot's advice in a game in which one can win or lose money (Mileounis, Cuijpers, & Barakova, 2015). In similar setting, trust in the robot advices was discussed by Aroyo, Rea, and Sciutti (2017) and the impact of the embodiment on the level of trust in robot recommendations was discussed by Maris, Lehmann, Natale, and Grzyb (2017). The experimental choice task in our study was designed to be unrelated to the daily life activities and interests of the participants such as health care or humanity issues, to ensure a uniformly low level of psychological involvement in the choices made. Persuasion in low psychological involvement is crucially needed especially in persuading people to join some activities that may not give any benefit to the doer, but valuable for other application domains towards the society such as volunteering work and blood donation campaign. Also, in the present case, it helps to ensure that the results are not confounded by individual differences regarding participants' attitudes towards the choice behaviour.

In our study, an advisor with three different levels of social agency was assigned to each of the participants (high: a robot with social cues and a text display, medium: a robot with no social cues except the blinking eyes and text display and low: text display only). The advisor (also referred to as social agent) exhibited two different coerciveness of language (high: forceful language and slight: pleasant language). There were ten tasks to be completed by participants during the game and the objective of the advice for each task was the same; to persuade the participants to change their initial decision. At the end of the game, the participants were asked to answer a questionnaire that was developed to measure their psychological reactance level based on the feelings of anger and negative cognitions scores.

The first hypothesis (H1) predicted that there is a significant difference in terms of psychological reactance score between the participants who received the advice in highly coercive language and those who received the advice in slightly coercive language. This was confirmed by the experiment since there was significant relationship found between those variables when the reactance elements treated as individual measure. Participants felt more anger when the advisor used forceful (highly coercive) language to persuade them but did not report as much negative thoughts as in the slightly coercive language condition (see Table 1). A possible explanation for this result could be that the threat level between those two levels of coerciveness of language was not strong enough to cause detectable effect on the measured reactance. This finding contradicted the outcomes of earlier works which found that highly coercive language could provoke higher psychological reactance (Quick & Considine, 2008; Roubroeks et al., 2009).

A significant relationship was found between both social agency and coerciveness of language upon psychological reactance as expected in the second hypothesis (H2). In the slightly coercive language condition, the reactance score increased according to the level of social agency. This trend did not occur in the highly coercive language condition (refer to Figure 3.4). However, the feelings of anger in all three levels of social agency increased according to the levels of coerciveness of language. A possible explanation could be that participants did not feel irritated when the robot started to give advice in highly coercive language since they believed the robot looked knowledgeable and capable to help them to select the best answer. People could be unsure which option in the game was the right one or did not mind so much (low psychological involvement), and they would just follow the advisor to change their initial answer. Thus, there were fewer negative cognitions reported against the higher social agency after the game although the language used by the social agent was unpleasant as emphasized in the third hypothesis (H3). This explanation is strongly supported by the results in the decision making in which most participants tend to change their answer when highly coercive language was used compare to slightly coercive language (see Figure 3.5). Participants might dislike to be pushed around, but when the higher social agent asked them to do a task, they would just do it!

In addition, the effect of social agency manipulation also could not be established as the source of psychological reactance, since there was no significant relationship found between those two variables. However, one of the participants in high social agency condition confidently express his/her thought about the ability of the SociBot to be the best future advisor; meanwhile several participants in the low and medium social agency conditions thought of their advisor as a boring agent and they even doubted on the personality of their advisor. This finding contradicted with earlier research that indicated the higher number of social cues used giving advice could increase the level of psychological reactance (Liu, Helfenstein, & Wahlstedt, 2008; Roubroeks et al., 2011; Roubroeks et al., 2009). This could be due to the advice that was displayed on the screen during the interaction in high and medium social agency conditions. Actually, we decided to keep the screen based display in all three social agency conditions, also when the SociBot was present, to avoid any effect of perception towards the dimensionality (2D or 3D) of the agent used in this experiment (Segura, Kriegel, Aylett, Deshmukh, & Cramer, 2012). Especially in the high social agency condition, the robot successfully caught the participants' attention by looking at them while conveying the advice and while expressing verbal and nonverbal social cues. Analysis of the video recording of participants' showed that in the medium and high social agency conditions, participants split their attention between the robot and the screen. A small number of them would read the text while listening to the advice recited by the social agent, which may have reduced the impact of the facial expression in the high social agency condition. Future studies could avoid this problem by avoiding the use of textual display all together, so that the full attention of the participants be directed to the social robot, in which case social agency more indeed enhance the persuasive effectiveness of the robot.

3.5 Summary

We conclude this chapter with a gleam of hope on the application of social robots in persuading people. This study demonstrated that adding social cues mitigate the psychological reactance to highly coercive language. Additionally, highly coercive language leads to compliance regardless of the other social cues a robotic persuasive agent can display, such as facial expression. These findings may help persuasive robots designers tailor the coerciveness of language used by persuasive robot to be high for increasing the chances of successful persuasive attempts.

While coerciveness language appeared to be an important social cue for higher chances of compliance, no evidence to support Social Agency theory (Mayer et al., 2003) was found in this study. That is, higher numbers of social cues displayed by persuasive agents did not trigger higher social responses as expected. We argue that people might need to be more involved in the task at hand for this effect to occur. This prompts the need for another study to test the Social Agency theory (Mayer et al., 2003) when the persuader is a social robot. Therefore, in the next chapter, we discuss the effect of the number of social cues and the degree of task involvement on human social responses (psychological reactance and compliance) in detail.

CHAPTER 4

Mind Your Own Business! More Social Cues Cause More Social Responses

This chapter is based on a published paper:

The influence of social cues in persuasive social robots on psychological reactance and compliance (2018). *Computers in Human Behavior*, 87, 58-65. DOI: 10.1016/j.chb.2018.05.016

As demonstrated in Chapter 3, the persuasive power of artificial social agents in persuasive attempts can be increased by employing highly coercive language. However, we did not find any proof to support the Social Agency theory (Mayer et al., 2003). A couple of limitations of the experiment design may be the reason for this. First, some participants reported that in the social agency conditions- it was too hard to focus on the advisory-text and the social cues provided by the persuasive robot at the same time. Thus they may have not perceived the cues limiting the intended perception of social agency. Additionally, they were asked to create a drink for an alien in the decision-making tasks, in which they did not care much about it. This limited involvement in the task may have made them very susceptible to persuasive attempts by the robot thus obscuring differences that were caused by different levels of social agency. To provide a more valid test of the social agency theory, we designed a laboratory experiment to asses psychological reactance and compliance to persuasive attempts delivered by similar agents as in the earlier study: an artificial (non-robotic) social agent, a social robot with minimal social cues (human-like face with speech output and blinking eyes), and a social robot with enhanced social cues (human-like face with emotional intonation voice, head movement and facial expression). Participants were asked either to create a drink for an alien or to create a drink for themselves; we compared psychological involvement on social responses to the agent. Our results suggested that a social robot presenting more social cues will cause higher reactance and this effect is stronger when the user feels involved in the task at hand.

4.1 Introduction

In this chapter, we aim to evaluate the effect of social cues of an agent upon psychological reactance and compliance as well as the level of involvement of a person with the issue at hand. It can be expected that when an agent limits a person's freedom about an issue they are not involved in, psychological reactance may be lower or not occur, but when a person's freedom is limited about an issue in which that person is strongly involved, they may experience stronger reactance. Several studies have investigated the effects of involvement towards humans' psychophysiological responses in an interactive game (Lim & Reeves, 2009) like engagement level between gameplays with avatars or computer agents (Lim & Reeves, 2010) and persuasion (Johnson & Eagly, 1989; Oreg & Sverdlik, 2014). From those studies, it can be concluded that in high-involvement situations, the chances for successful persuasion activities are low. In contrast, in low-involvement situations, chances for successful persuasion might be higher. Nevertheless, earlier research has not yet examined the effect of involvement upon psychological reactance.

In line with Social Agency theory (Mayer et al., 2003) and the Media Equation hypothesis (Reeves & Nass, 1996), we expected that people would be more socially responsive to the agent that has stronger (or more) social cues. Counter intuitively and in contrast to earlier psychological reactance studies (e.g. Roubroeks et al. (2009)), our study reported in Chapter 3 found that robotic agents evoked less reactant responses when using unpleasant language (highly coercive language) in persuasive messages. That is, the reactance towards a robotic agent that used forceful language to persuade people was lower when the robotic agent displayed some social cues. Nevertheless, this earlier study (cf. Chapter 3) did not show that people responded in more social ways (i.e., show more psychological reactance) when a social robot displayed more social cues in delivering the forceful persuasive message. The external validity of that experiment can be criticized as the decision that experimental participants had to make pertained to an artificial task with little at stake for them. Specifically, the experimental task was to decide upon the constitution of a drink for an imaginary alien, a choice behavior for which the participants did not care about. We claimed in an earlier study (cf. Chapter 3) it was done to avoid confounding effects of psychological involvement with the task at hand. However, it leaves the question open whether the results can be replicated in case the participants have higher involvement with the given tasks.

Thus, this chapter build on and extend our study in Chapter 3 which compared social agents that are endowed with three different levels of social cues. We aim to address the limitations of that earlier study as discussed above, and to consolidate current understanding regarding the effects of social cues on social responses as suggested by Social Agency theory (Mayer et al., 2003). We report an experiment that compares the situations of high and low psychological involvement in persuasion activity in different social agency conditions. The following sections motivate the method and describe the results of this study. We conclude with a discussion regarding the implications of our findings for the field of persuasion in human-robot interaction applications and research on psychological reactance.

The Current Study

The experimental set up involved a human-agent interaction in which the participants were asked to make decisions in a fantasy game environment, similar to the task in Chapter 3. Participants were required to make an initial selection of a drink, after which an artificial agent would attempt to convince them to modify their choice. Highly coercive language was used by the social agent in conveying the advice throughout the study. This was done to obtain higher chances of compliance in persuasive attempts as reported in Chapter 3. The experiment aimed to test the following two hypotheses:

- H1. There is a significant difference in psychological reactance score between participants in the high psychological involvement game and those who receive the same advice in a low psychological involvement game, especially when the advisor has higher social agency
- H2. There is a significant difference in compliance score between participants in the low psychological involvement game when being advised by an agent with a high social agency and those in high psychological involvement game receiving feedback by the same agent.

4.2 Materials and Methods

4.2.1 Participants and Design

Sixty participants were recruited as volunteers from a local participant database with ages ranging from 18 to 37 years old (41 males and 19 females; age $M = 23.98$, $SD = 3.71$). The participants were randomly assigned to one condition of a 3 (social agency: high vs. medium vs. low) by 2 (psychological involvement: high vs. low) between-subjects experimental design. Each participant received a €10 voucher as a token of appreciation at the end of the session which lasted forty minutes on average.

4.2.2 Manipulations

Manipulation of Social Agency

The manipulation of social agency was based on the number of social cues portrayed by the agent as in Chapter 3. As reported in the previous chapter, some of the participants mentioned that they had hardly noticed the social cues provided by the robot especially in the medium social agency condition their attention was directed to reading the text provided to them. Additionally, participants in the high social agency claimed that they needed to divide their attention between the text on the screen and the robot talking to them. Accordingly, we did not provide a text to participants in the medium and the high social agency conditions in the study. This we hoped would allow participants to direct their attention to the robot's face. Thus, in this study, the persuasive-text was only provided in the low social agency condition. Further, verbal cues (a monotone voice) were added to the robot in the medium social agency condition. By removing the persuasive-text in the medium and high social agency conditions, the source of the persuasive messages was only the robot. An overview of the social agency manipulation used in this study is shown in Figure 4.1.

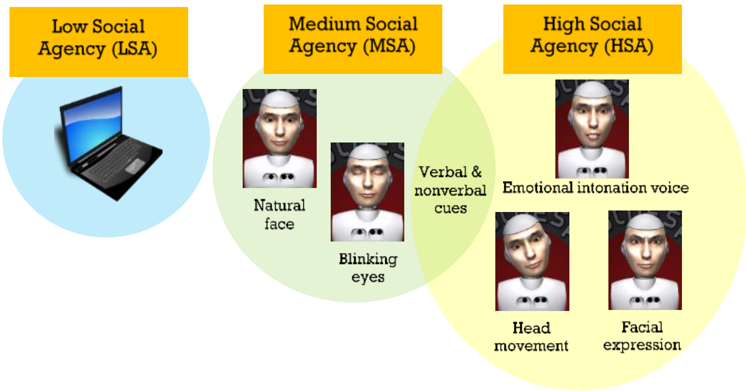
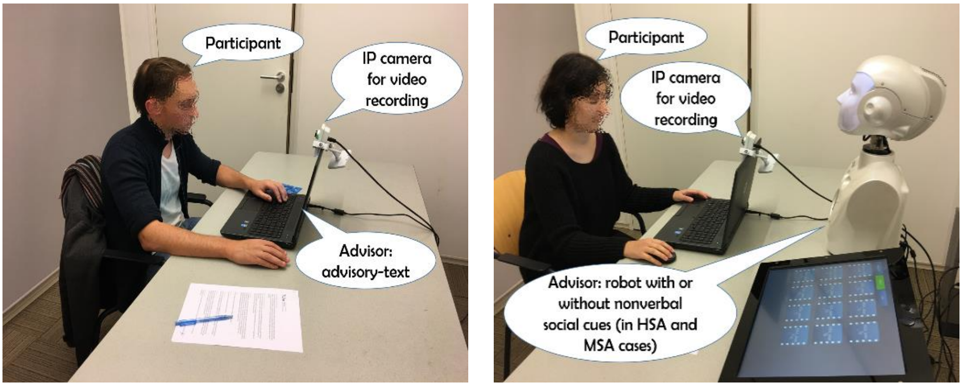


Figure 4.1: Manipulation of social agency conditions.

The manipulation of social agency includes (1) low social agency: absence of a robot - the advice was displayed on a screen as an advisory-text (2) medium social agency: a robot with a human-like face that spoke with monotone voice and showing minimal nonverbal cues (blinking eyes) (3) high social agency: the robot gave advice using several verbal and nonverbal social cues including head movement (e.g., nodding the head), facial expression (e.g., looking away indicates the robot was thinking) and emotional intonation in the voice.

Similar to the experimental set up in Chapter 3, a SociBot was placed in front of the participants in medium and high social agency conditions (refer to Figure 4.2) for delivering the persuasive messages.



(a) (b)

Figure 4.2: Experimental set ups
(a) Low Social Agency (LSA)
(b) Medium Social Agency (MSA) and High Social Agency (HSA).

Manipulation of Psychological Involvement

As mentioned already, participants were exposed to either of two levels of psychological involvement, which we label as low and high, based on the degree of expected relevance of the tasks to the participant. In the low psychological involvement game, the participants were asked to create a drink for an alien while participants in high psychological involvement game were required to create a drink for themselves (to drink after the experiment). The examples of highly coercive, forceful language advice for both psychological involvement level provided by the respective social agent as follows (a) Low psychological involvement: *'What a bad choice. The structure of the drink you chose before was very bad for* ***the alien's*** *health condition. You must serve other drink to the alien. I am sure* ***the alien*** *will love it!'* (b) High psychological involvement: 'W*hat a bad choice. The structure of the drink you chose before was very bad for* ***your*** *health condition. You must choose other drink. I am sure* ***you*** *will love it!'*

4.2.3 Task

The task for this study was the same as in Chapter 3: 'Beverages Creation Station'. The participants were asked to create a drink based on the psychological involvement game assigned (low: alien's drink vs high: own drink as elaborated earlier). The social agent used highly coercive language (unpleasant and pushy language) all the time in expressing the persuasive advice towards the participants to change their initial selection to other choices as their final answer. Although the psychological involvement was manipulated in this experiment, the core concept of the advice made by the social agent was kept as ambiguous as possible. An example of the recommendation in low social agency session for high psychological involvement game was *'What a childish selection!* ***You*** *cannot even finish up the whole drinks if* ***you choose*** *a big container so in the end that delicious drink will just be thrown away. It is a waste. However, if* ***you*** *choose a small container,* ***you need*** *to pay some amount of money to get other drinks. Just choose another container that contained a right* *amount of drinks which fit* ***your*** *tummy appropriately. Do not be too greedy, but at the same time, do not be too absurd'.*

4.2.4 Procedure

The experiment took place a dedicated room. Arriving participants provided consent and demographic information before they were introduced to the social agent corresponding to the experimental condition they were assigned to. As in Chapter 3, a SociBot was placed in front of participants assigned to the medium and the high social agency conditions; during the demonstration session they were shown how the SociBot delivers advice. For the low social agency condition session, there was no robot present, and the advice would come in the form of advisory-text on a laptop screen.

Participants were reminded about the psychological involvement level assigned to them in each task. Let's say they were in the low psychological involvement condition where a drink should be made for the alien; then a reminder would be presented in the laptop screen displaying the game: *'Please remember! The drink is for the* ***ALIEN****, not for* ***YOU****'.* In contrast, in the high psychological involvement condition, the participants would be prompted with a message reading as follows: *'Please remember! The drink is for* ***YOU****, not for* ***OTHERS****'* (refer to Figure 4.3).

Finally, after finishing the game and answering the questionnaires required in Google form, the experimenter would return to the room and present a token of appreciation (worth €10) to each participant. The session officially finished after the experimenter debriefed the participants.

4.2.5 Measures

We used the same questionnaires as in Chapter 3 to measure perceived threat to autonomy (Walter & Lopez, 2008), psychological reactance (Dillard & Shen, 2005; Quick & Stephenson, 2007b) and compliance scores.

Apart from that, another manipulation check was done to check whether the manipulation of psychological involvement affects the level of immersion towards the game created. An adaptation of two different questionnaires developed by earlier research (Mittal, 1989; van Wijngaarden et al,. 2000) was made for evaluating how strong the associated immersion was experienced by the participants during the game. Participants were asked to answer five immersion questions about the degree of importance, concern, involvement, care, and responsiveness towards the decision taken about making a tasty drink. Participants could answer on a 5-point Likert Scale ranging from (1) completely disagree to (5) completely agree.

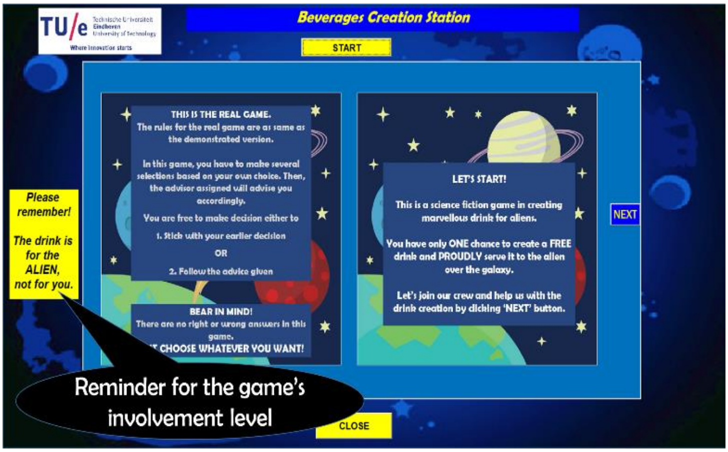


Figure 4.3: GUI of the game.

4.3 Findings

4.3.1 Manipulation Check

ANOVA tests were conducted to check whether the variation of social agency and psychological involvement caused differences in the level of perceived threat to autonomy in making decisions and the level of immersion towards the game.

Perceived Threat to Autonomy

First, we checked whether the participants perceived the manipulation of social agency as a threat to their autonomy in making decisions. No significant effect of the social agency manipulation was found on perceived threat to autonomy, $F(2,58) = 0.88$, $p = 0.42$. This finding indicates that the level of social agency of the agent did not influence the extent to which participants felt threatened.

In addition, the main effect of psychological involvement on perceived threat to autonomy was significant, $F(1,59) = 4.26$, $p = 0.04$, with low psychological involvement: $M = 3.90$ ($SD = 0.55$) and high psychological involvement: $M = 3.58$ ($SD = 0.64$). Results showed that the participants in the low psychological involvement game (making the alien's drink) perceived the advice given by the social agent as a threat, more than the participants in the high psychological involvement game (creating own drink).

Immersion

Second, we checked whether the manipulation of psychological involvement was successful. Results indicated that psychological involvement has a significant contribution to the level of immersion experienced, $F(1,59) = 3.87$, $p = 0.05$, low psychological involvement: $M = 3.69$ ($SD = 0.83$) and high psychological involvement: $M = 4.07$ ($SD = 0.63$). These results showed that the participants in the high psychological involvement game (creating one's own drink) were much more immersed in the game compared to other participants who were in the low psychological involvement game (creating the alien's drink). This result confirmed that ostensibly making a drink for an alien versus oneself was an effective manipulation of psychological involvement.

Additionally, no significant main effect of social agency was found on the level of immersion, $F(1,59) = 3.87$, $p = 0.60$ (*n.s*). Results indicate that the level of social agency did not influenced the level of immersion towards the game.

4.3.2 Hypothesis Testing

Hypothesis 1: Psychological Reactance

Repeated measures of psychological reactance consisting of two components (feelings of anger and negative cognitions[1]) were used to investigate the first hypothesis. First, a Pearson product-moment correlation test between feelings of anger and the rate of self-reported negative cognitions demonstrated that there was a weak correlation between these two variables ($r = 0.16$, $n = 60$, $p = 0.22$ (*n.s*)). This is in line with earlier research (Dillard & Shen, 2005), as they measure two aspects of the same phenomenon that cannot be completely separated from each other.

To test hypothesis 1, a repeated measures ANOVA test was run with social agency and psychological involvement as the independent variables and psychological reactance score as the dependent variable. The two components of psychological reactance were treated as a repeated measures factor as in Chapter 3.

As a result, the manipulation of psychological involvement level was found to have a significant effect upon the measured psychological reactance, *Wilks' Λ* = 0.92, $F(1, 48) = 4.32$, $p = 0.04$, partial $\eta^2 = 0.08$.[2] Besides, the social agency level also had a significant influence on the psychological reactance, *Wilks' Λ* = 0.74, $F(2, 48) = 8.20$, $p = 0.001$, partial $\eta^2 = 0.26$. Post hoc comparisons using the Bonferroni correction indicated that the mean score of psychological reactance for the low social agency condition ($M = 10.12$, $SD = 9.17$) did not significantly different than the medium social agency condition ($M = 4.65$, $SD = 10.20$), $p = 0.81$. The mean score for the high social agency condition ($M = 17.64$, $SD = 10.20$) was significantly differ from the medium social agency condition, $p = 0.01$, but did not significantly different than the low social agency condition, $p = 0.15$. More importantly, there was a significant interaction between social agency and psychological involvement manipulations on psychological reactance, *Wilks' Λ* = 0.84, $F(2, 48) = 4.14$, $p = 0.02$, partial $\eta^2 = 0.16$ (see Figure 4.4).

Several conclusions can be drawn from this analysis. First, concerning the psychological involvement, psychological reactance recorded in making one's own drink ($M = 13.45$, $SD = 9.75$) was higher than in making the alien's drink ($M = 8.16$, $SD = 9.97$), especially when the appointed advisor was a robot in the high social agency condition. Meanwhile, there was a similar

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[1] The score for feelings of anger showed no outlier and was normally distributed. However, the score for negative cognitions was not normally distributed. We proceeded to use the repeated measures ANOVA for testing the first hypothesis because (in line with statistical insights (Glass, Peckham, & Sanders, 1972; Harwell, Rubinstein, Hayes, & Olds, 1992; Lix, Keselman, & Keselman, 1996) the score for negative cognitions was distributed similarly (non-normally) in all of the 3 x 2 cells, and because ANOVAs are considered fairly "robust" to deviations from normality.

[2] In the Hypothesis 1 analysis, we used gender as an additional predictor, because we assumed it to explain variance of the manipulations of social agency and psychological involvements. However, since we did not have any hypothesis about the effects of gender, we did not report its effects.

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reactance score for participants in the low social agency condition for both making their own and the alien's drinks. Second, with respect to the level of social agency, participants in the high social agency conditions experienced the highest psychological reactance, followed by the low social agency condition and the lowest reactance was in medium social agency condition. Figure 4.4 also indicates that participants who made their own drink while interacting with a high social agency advisor recorded the highest psychological reactance. The lowest psychological reactance was experienced by participants in the medium social agency condition. Importantly, there was a clear increment of psychological reactance level (the differences of psychological reactance mean values) with the increment of social agency's level.

An exploratory analysis examined the individual effects of psychological reactance score (feelings of anger and negative cognitions as two separate dependent variables) resulting from the manipulations of social agency and psychological involvement using two separate two-way ANOVA test. A significant interaction was found between social agency and psychological involvement for the negative cognitions score, $F(2,48) = 4.35$, $p = 0.02$, partial $\eta^2 = 0.15$. Also, there was a statistically significant difference in the negative cognitions score between the low, medium and high social agency conditions for the high psychological involvement game, $F(2,48) = 10.43$, $p = 0.001$, partial $\eta^2 = 0.30$. However, the simple main effect of the social agency on the mean negative cognitions score for those who participated in the low psychological involvement game was not statistically significant, $F(2,48) = 1.61$, $p = 0.21$, partial $\eta^2 = 0.06$. Post hoc comparisons using the Bonferroni correction indicated that the mean score of negative cognitions for the low social agency condition did not significantly different than the medium social agency condition, $p = 0.82$. The mean score for the high social agency condition was significantly differ from the medium social agency condition, $p = 0.01$, but did not significantly different than the low social agency condition, $p = 0.14$. Additionally, the mean of negative cognitions in the high psychological involvement's game ($M = 22$, $SD = 23.1$) was significantly higher than in the low psychological involvement game ($M = 16.67$, $SD = 16.67$), $F(1,48) = 4.39$, $p = 0.04$, partial $\eta^2 = 0.08$.

As for feelings of anger, there was no statistically significant interaction between social agency and psychological involvement, $F(2,48) = 0.22$, $p = 0.81$, partial $\eta^2 = 0.01$. We also found no significant main influence of social agency (the first ANOVA) and psychological involvement (the second ANOVA) on the reported feelings of anger, $F(2,48) = 0.03$, $p = 0.98$ and $F(2,48) = 0.03$, $p = 0.86$ respectively. As such, these results demonstrated that the lowest feelings of anger were experienced by participants in the low psychological involvement game while interacting with advisor in with low social agency condition ($M = 3.10$, $SD = 0.74$). On the other hand, the highest feelings of anger recorded by participants playing the high psychological involvement game in the low social agency condition ($M = 3.25$, $SD = 1.21$).

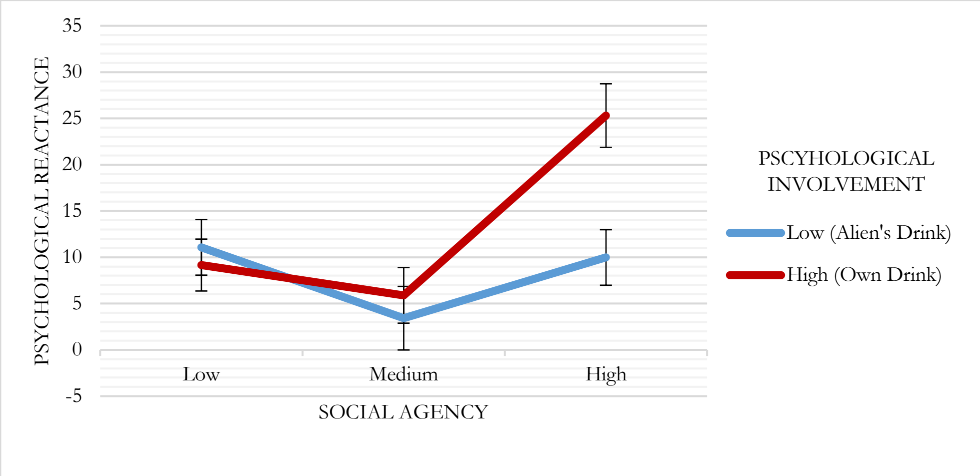

Figure 4.4: Mean and standard error of psychological reactance scores by social agency (low vs. medium vs. high) and psychological involvement (low vs. high).

Hypothesis 2: Compliance

The second hypothesis stated that there is a significant difference in compliance score between participants who were advised by the agent with high social agency, especially those who played the low psychological involvement game and the participants playing the high psychological involvement game. To test the effect of both social agency and psychological involvement manipulations on compliance score, a two-way ANOVA test was conducted. The result revealed that there was no significant interaction of social agency and psychological involvement manipulations on the compliance, $F(2,54) = 0.42$, $p = 0.66$, partial $\eta^2 = 0.02$. It is interesting to note that the relationship was statistically significant when the manipulation of psychological involvement was the only independent variable used with the compliance score as the dependent variable using ANOVA, $F(2,54) = 35.43$, $p < 0.001$, partial $\eta^2 = 0.40$.

The pattern of compliance (summation of all task's score) based on the manipulations of social agency and psychological involvement can be observed in Figure 4.5. By comparing all conditions, participants who were advised by an agent with high social agency in a high psychological involvement game showed the highest noncompliance by neglecting most of the given advice. Univariate tests revealed a significant simple effect of psychological involvement within each level combination of social agency manipulation towards compliance score. These tests demonstrated that there were statistically significant difference in compliance scores between low psychological involvement and high psychological involvement games onto compliance using between-subject advisor in low social agency $F(1, 54) = 8.36$, $p = 0.01$, partial $\eta^2 = 0.13$, medium social agency $F(1, 54) = 10.69$, $p = 0.002$, partial $\eta^2 = 0.17$ and high social agency $F(1, 54) = 17.22$, $p < 0.001$, partial $\eta^2 = 0.24$.

Regarding the manipulation of social agency, although there were only small differences in compliance scores between the three social agency levels (low vs. medium vs. high social agency), the participants in the medium social agency condition ($M = 5.00$, $SD = 2.47$) showed the highest cumulative compliance score. Whereas, participants that interacted with the robot with enhanced social cues in high social agency condition were the least compliant ($M = 4.45$, $SD = 2.04$). This result is in agreement with the psychological reactance measured in the first hypothesis, in which the participants in the medium social agency condition experienced the lowest reactance compared to other social agency conditions.

Regarding psychological involvement, the participants who were making their own drink (high psychological involvement) refused to follow the advice more often ($M = 3.40$, $SD = 1.54$, total compliance score of 102) than those making the alien's drink ($M = 6.13$, $SD = 1.92$, total compliance score of 168). Additionally, there was no consistent pattern to show that the compliance changes over time (based on the task number) for both manipulations of social agency and psychological involvement. Although the social agent kept on disagreeing with the participants' initial choice at every single decision point, the compliance score was not influenced by the behaviour of the social agent over time. In other words, the advisor has no less of an impact over time in the decisions made by the participants.

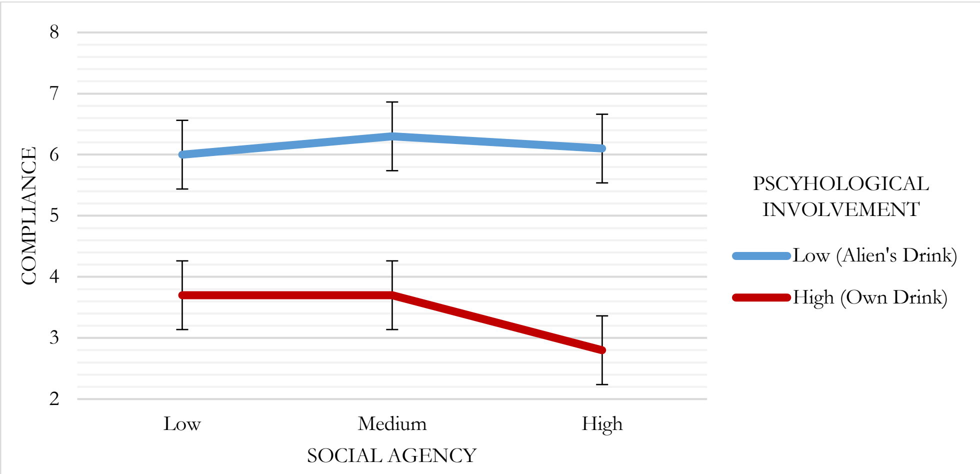

Figure 4.5: Mean and standard error of compliance scores by social agency (low vs. medium vs. high) and psychological involvement (low vs. high).

4.4 Discussion

The primary purpose of this chapter was to investigate human social responses (psychological reactance and compliance) on several social agency conditions in persuasion. In line with the Social Agency theory (Mayer et al., 2003), we expected that social agents with stronger (or more) social cues would elicit higher social responses such as psychological reactance compared agents with minimal or no social cues. In this chapter we also compared the difference in social responses experienced by humans when they were put in a situation of either high or low psychological involvement.

Hypothesis H1 was confirmed only partly. We found that as the level of social agency and psychological involvement increased, psychological reactance would increase as well, in line with earlier research (Roubroeks, Midden, & Ham, 2009; Roubroeks, Ham, & Midden, 2011). Contrary to our expectations, an agent with medium social agency, (i.e., with minimal social cues) provoked the lowest psychological reactance in both psychological involvement conditions (refer to Figure 4.4). We assume that high social agency advisor evoked the highest reactance because of the forceful voice tone and pressure portrayed by the robot that attempted to convince participants into changing their choices for each task. A possible explanation why the psychological reactance in medium social agency condition was lower than in the low social agency is that in the medium social agency case, the absence of facial expressions and the unemotional intonation of the robot, could be perceived as a less forceful way to deliver advice, compared to text which participants could assume/imagine to be delivered forcefully as they were reading it. This result can be explained by the finding that some of the participants indicated that they had experienced that the advice was delivered in a forceful tone, high pitch which may have caused higher psychological reactance to happen (compared to the medium social agency condition). Apart from the low social agency condition, the psychological reactance in the low psychological involvement game was always lower than in the high psychological involvement game, as participants would experience higher psychological reactance when they were pushed to change the choice of their own drink. There could be two explanations for this: participants may be more receptive to advice in the low psychological involvement condition as they did not know what drink aliens like best or because they did not care as much for what drink the alien will have (the participants might be in the state of 'open for persuasion': as discussed in Kooijmans and Rauterberg (2006)). However, as they knew more what they like to have compared to the persuader (the social agent) in the high psychological involvement game, they felt more anger and had more negative cognitions towards the agent when they were pushed to change their choices.

The second hypothesis suggested that there is a significant difference in compliance score between participants that made own drink in the game (high psychological involvement) than those in the low psychological involvement game. Results demonstrated that the manipulation of psychological involvement has a statistically significant effect upon the compliance score, but failed to reveal any such effects with the manipulation of social agency. By referring to Figure 4.5, it can be observed that the participants preferred to follow the advice for the alien's drink (independent of the level of social agency) perhaps because they believed that the advisor knew the alien's preference better than themselves. In contrast, when the participants were asked to create their own drink, as they were very sure of what they would want to have; advice from the social agent was always disregarded. Thus, the compliance recorded during the high psychological involvement game was always lower than in the low psychological involvement game.

The most important finding emerging from these two hypotheses is that the differences of psychological reactance (discussed in Hypothesis 1) and compliance (discussed in Hypothesis 2) scores between low and high psychological involvement games increased with the addition of social cues in the agents (see Figure 4.4 and Figure 4.5 respectively). It showed that social cues displayed in the higher social agency condition influence people to consider the agent as a real human during the interaction (Blascovich, 2002b; Martin, 1997). This finding also is in agreement with Social Agency theory (Mayer et al., 2003) which argues that the stronger (or more) social characteristics a robot can display, the higher the social responses that humans will exhibit during human-robot interaction.

4.5 Summary

The main finding of this chapter provides insight into the increment of social responses (psychological reactance and compliance reactions) towards technology parallel with the increment of social cues exhibited by the agent especially when the participants are psychologically involved with the matter or the given task. This notion aligns with Social Agency theory (Mayer et al., 2003). The research outcomes also indicated persuasion activity using artificial social agent could cause higher psychological reactance and lower compliance towards the persuasive attempts as is the case in human-human interaction.

To accommodate the overarching research questions of this thesis, we further combine the data pertaining to the same hypotheses in Chapter 3 and Chapter 4. This combination of data sets will be implemented and reported in Chapter 5 by investigating the desirable number of social cues for persuasive robots so that the persuasive attempts will be effective and positively perceived by humans.

CHAPTER 5

Poker Face Influence: Persuasive Robot with Minimal Social Cues Triggers Less Psychological Reactance

This chapter is based on a published paper:

Poker face influence: Persuasive robots with minimal social cues triggers less psychological reactance (2018, August). Paper presented at 27th *IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, 2018 (pp. 940-946). DOI: 10.1109/ROMAN.2018.8525535

In this chapter, we investigate the effect of social cues implemented in artificial persuasive agents on psychological reactance and compliance. We combined the data points from the experimental studies described in Chapter 3 and Chapter 4 to understand the influence of the number of social cues on social responses (psychological reactance and compliance) toward robotic persuaders. As a recap to the earlier studies, participants in a laboratory experiment played a decision-making game in which persuasive attempts were delivered in one of three forms: as persuasive-text, through robot displaying minimal social cues, or by the same robot displaying enhanced social cues. Results suggest that a persuasive robot with minimal social cues invokes the lowest reactance. Remarkably, an exploratory analysis indicated cross-gender effects (between robot and user) upon invoking lower psychological reactance, with female participants demonstrating higher compliance than male participants.

5.1 Introduction

In line with the Media Equation hypothesis (Reeves & Nass, 1996), people have been shown to respond socially to the social actors. An earlier study (Roubroeks et al., 2009) demonstrated that people experience psychological reactance (an example of social responses) towards persuasive agents (an example of social actors). Social Agency theory (Mayer et al., 2003) suggested that enhancing the social cues by increasing the number of social characteristics of an artificial social agent will evoke higher social responses in users. This theory is supported by earlier studies in several contexts for example in comparison between human voice vs synthethic voice (Atkinson et al., 2005; Barakova et al., 2018; Roubroeks et al., 2011). Earlier studies of psychological reactance towards artificial agents suggested that the level of social agency (Roubroeks et al., 2011), the social skill of the agent (Liu et al., 2008), the use of controlling language and lexical concreteness (Miller et al., 2007) are some of the main factors influencing the level of psychological reactance (Ehrenbrink & Prezenski, 2017).

We also performed a similar experiment as in (Roubroeks et al., 2009) involving a realistic interaction between humans and a robot in Chapter 3 and Chapter 4. In these experiments, the participants were asked to play a decision-making game while interacting with agents with three different social agency levels: (i) at the lowest agency level they were presented with plain text with a persuasive message (ii) at the medium social agency level they interacted with a robot featuring minimal social cues (iii) at the highest social agency level they interacted with the same robot featuring enhanced social cues. In Chapter 3, we found that highly coercive, forceful language was more persuasive in encouraging the participants to comply with the advice given than slightly coercive language. Nevertheless, this study provided no clear evidence of the significance of social agency levels as the source of psychological reactance, as demonstrated in earlier study (Roubroeks et al., 2009) due to the small sample size. On the other hand in Chapter 4, we found that the increment of psychological reactance towards technology parallel with the increment of social cues exhibit by the agent. Nevertheless, this study only provided clear evidence of the significance of social agency levels as the source of psychological reactance when the participants are highly involved with the matter or the given task. Overall, both studies in Chapter 3 and Chapter 4 did not show that enhanced social cues in the advisor lead to higher psychological reactance as would be anticipated by the Social Agency theory (Mayer et al., 2003) in low psychological involvement task.

The Current Study

Based on our overarching research question, in this chapter, we focus on the question whether the number of social cues implemented in persuasive agents influences how effective they will be in persuading humans and whether they are positively perceived by humans. We pooled out the data points from Chapter 3 that have the same hypothesis with Chapter 4 in analyzing the psychological reactance and compliance experienced by the participants from the manipulation of social agency. This chapter aimed to test the following two hypotheses:

H1. There is a significant difference in psychological reactance score between participants who being advised by the agent with higher social agency and those who being advised by the agent with lower social agency

H2. There is a significant difference in compliance score between participants who being advised by the agent with lower social agency and those who being advised by the agent with higher social agency

5.2 Materials and Methods

5.2.1 Participants and Design

Sixty data points were pooled out based on data collected in the experiments described in Chapter 3 and Chapter 4. The age of participants ranged between 18 and 55 years old (*M* = 22.5, *SD* = 6.42, 38 males and 22 females). The combination of data points followed a 3-between-subjects design, corresponding to the three social agents: low vs medium vs high social agencies. Of the 60 participants, 30 participants are from the study of Chapter 3, and the other 30 participants are from the study of Chapter 4. 20 participants interacted with low social agent, 20 participants with medium social agent and the other 20 participants with high social agent. None of the participants in the study in Chapter 3 took part in the study in Chapter 4.

5.2.2 Manipulations

Manipulation of Social Agency

The manipulation of social agency was based on the number of social cues portrayed by the agent. As a recap, the manipulation of social agency in Chapter 3 includes (1) low social agency: absence of a robot - the advice was displayed on a screen as an advisory-text (2) medium social agency: advisory-text and a robot with a human-like face showing minimal nonverbal cues (blinking eyes and neutral face) (3) high social agency: advisory-text and a robot with several verbal and nonverbal social cues including head movement (e.g., nodding the head), faical expression (e.g., looking away indicates the robot was thinking) and emotional intonation voice.

On the other hand, the manipulation of social agency in Chapter 4 includes (1) low social agency: absence of a robot - the advice was displayed on a screen as an advisory-text (2) medium social agency: a robot with a human-like face that spoke with monotone voice and showing minimal nonverbal cues (blinking eyes and neutral face), and (3) high social agency: the robot gave advice using several verbal and nonverbal social cues including head movement, facial expression and emotional intonation of the voice (as a recap, please refer to Figure 5.1).

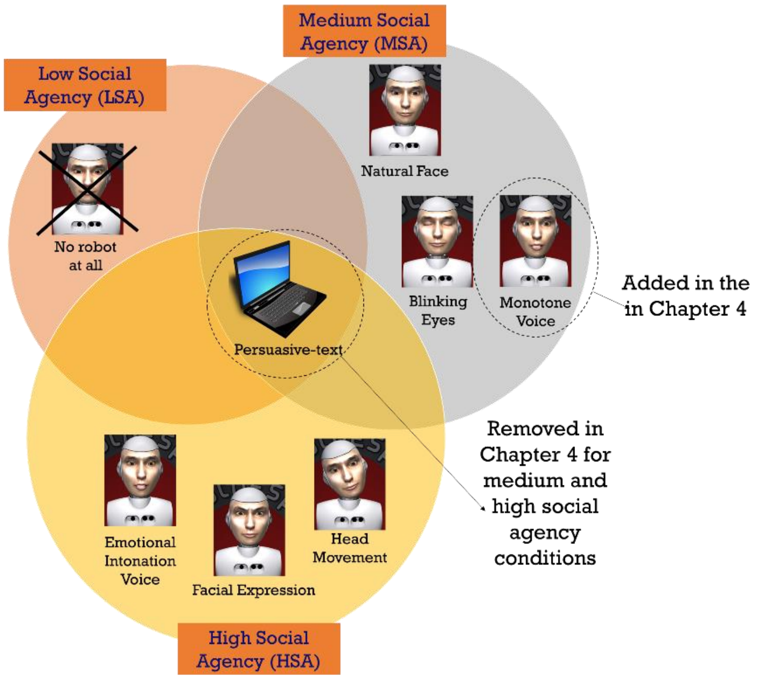

Figure 5.1: Comparison of social agency conditions used in Chapter 3 and Chapter 4.

5.3 Findings

5.3.1 Preliminary Check

A preliminary analysis showed that the manipulation of social agency in Chapter 3 and Chapter 4 were comparable. That is, a repeated ANOVA test showed no evidence for a statistically significant interaction effect between the independent variables (data collection from Chapter 3 and Chapter 4 $\times$ social agency) on the psychological reactance score (feeling of anger and negative cognitions), $F(2,54) = 0.50$, $p = 0.61$. Results indicated that the influence of social agency manipulation on a participant's psychological reactance did not differ between Chapter 3 and Chapter 4. Based on this result, we pooled together the data from the two studies for further analysis.

5.3.2 Hypothesis Testing

Hypothesis 1: Psychological Reactance

The first hypothesis was tested using a repeated measure analysis of the psychological reactance elements (negative cognitions and feelings of anger).[1] A repeated measure ANOVA test showed a main effect of social agency on psychological reactance, $F(2,15) = 5.01$, $p = 0.02$ (refer to Figure 5.2). Participants reported the highest reactance when interacting with the agent in the low social agency condition ($M = 12.51$, $SD = 5.57$), followed by the high social agency condition ($M = 8.68$, $SD = 5.63$) and the lowest reactance recorded by the medium social agency condition ($M = 6.07$, $SD = 5.75$). Pairwise comparisons found significant differences of reactance in the low and the medium levels of social agency, $p = 0.01$ using Bonferroni correction. The mean psychological reactance score was 6.44 points higher for the low social agency than for the medium social agency, with a 95% confidence interval [1.62, 11.26]. Post hoc comparisons using the Bonferroni correction indicated that the mean score of psychological reactance for the low social agency condition was significantly different than the medium social agency condition, $p = 0.004$. Also, the mean score for the high social agency condition was significantly differ from medium social agency condition, $p = 0.05$, but did not significantly different than low social agency condition, $p = 0.76$.

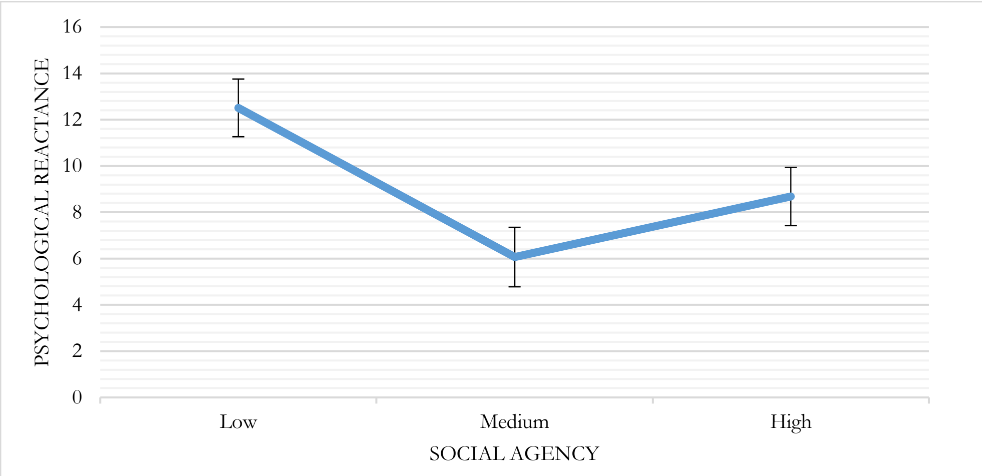

Figure 5.2: Mean and standard error of psychological reactance scores by the social agency (low vs medium vs high). Results show a significant main effect of social agency on psychological reactance.

Two separate ANCOVAs were employed to investigate the influence of social agency on the components of reactance: feelings of anger (the first ANOVA) and negative cognitions (the second ANOVA). The first ANOVA test showed a main effect of social agency on negative

[1] We used gender and responses to recommendations and advice as additional predictors in the first hypothesis (psychological reactance and its components) because we assumed it to explain variance of the manipulation of social agency. However, since we did not have any hypothesis about the effects of responses to recommendations and advice, we did not report its effects. We reported the effect of gender as an exploratory analysis only.

cognitions was significant, $F(2,15) = 5.42$, $p = 0.02$, partial $\eta^2 = 0.42$. Using the Bonferroni correction, pairwise comparisons revealed a significant difference in the mean negative cognitions scores in the low and the medium social agency conditions, $p = 0.01$. The score was 12.80 points higher for the low social agency condition than for the medium social agency condition, with a 95% confidence interval [2.96, 22.64]. Post hoc comparisons using the Bonferroni correction indicated that the mean score of negative cognitions for the low social agency condition was significantly different than the medium social agency condition, $p = 0.01$. However, the mean score for the high social agency condition did not significantly differ from the medium social agency condition, $p = 0.06$ and the low social agency condition, $p = 0.77$. Further, the second ANOVA showed no significant main effect of social agency was found on feelings of anger, $F(2,15) = 0.66$, $p = 0.53$, partial $\eta^2 = 0.08$.

Considering that the persuadee's gender might influence psychological reactance and compliance, two exploratory analyses were carried out. A repeated measures ANOVA showed a significant interaction effect of social agency and gender on psychological reactance, $F(2,15) = 7.26$, $p = 0.01$ (refer to Figure 5.3).

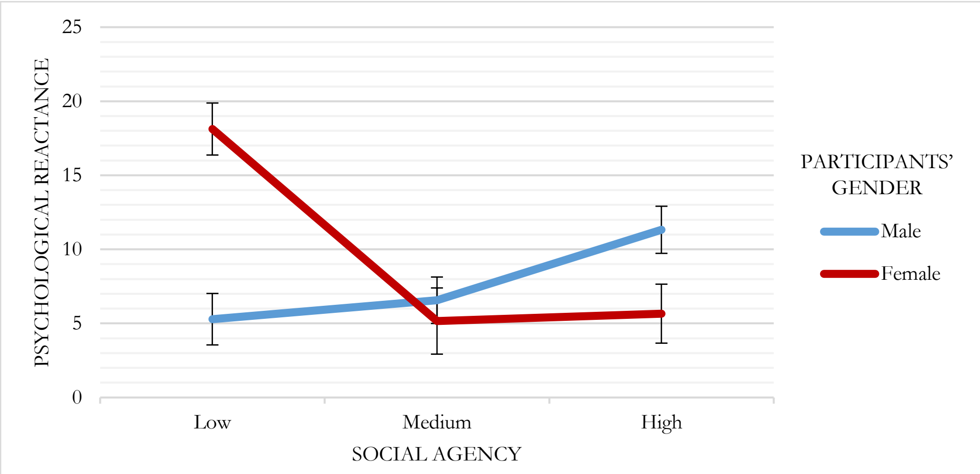

Figure 5.3: Mean and standard error of psychological reactance scores by the social agency (low vs medium vs high) and gender of the participants (male vs female). Results show a significant interaction effect of social agency and gender of the participants on psychological reactance. Male participants reported lower psychological reactance compared to female participants.

Figure 5.3 suggests that psychological reactance was triggered for male participants especially when interacting with a robot that provides several verbal and nonverbal cues (high social agency condition), $M = 11.32$, $SD = 5.73$. However, female participants experienced the highest psychological reactance when the persuasive advice was conveyed using text (low social agency condition), $M = 18.13$, $SD = 5.27$. The psychological reactance reported by female participants was lower when the robot delivered the persuasive messages, $M = 5.16$, $SD = 5.47$ for the medium social agency and $M = 5.66$, $SD = 5.27$ for the high social agency condition. Using the Bonferroni correction, pairwise comparisons for the psychological reactance score for females and males participants found significant differences, $p = 0.05$. The score was 3.10 points higher for the females than for the males, with a 95% confidence interval [-0.04, 6.25] (see Table 5.1).

Further exploratory analyses examined gender effects on negative cognitions. We found a statistically significant interaction effect of social agency and gender manipulations on negative cognitions, $F(2,15) = 7.22$, $p = 0.01$, partial $\eta^2 = 0.49$. Also a statistically significant difference was found between low, medium and high social agency conditions regarding negative cognitions by female participants, $F(2,15) = 14.20$, $p < 0.001$, partial $\eta^2 = 0.65$. The simple main effect of gender on mean negative cognitions score for male participants was also significant, $F(2,15) = 3.63$, $p = 0.05$, partial $\eta^2 = 0.33$ (see Table 5.2).

Table 5.1: Pairwise comparisons of psychological reactance scores between male and female participants based on social agency using Bonferroni correction.

Mean differences (Males - Females)	***SE***	**95% confidence interval for the difference**	
		Lower bound	***Upper bound***
Low social agency			
-12.84	2.47***	-18.10	-7.57
Medium social agency			
1.45	2.73	-4.41	7.22
High social agency			
5.66	2.55*	0.23	11.09

SE = standard error, ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 5.2: Pairwise comparisons of negative cognitions scores between low, medium and high social agency conditions based on gender using Bonferroni correction.

(A) Social agency	**(B) Social agency**	**Mean differences (A-B)**	***SE***	**95% confidence interval for the difference**	
				Lower bound	***Upper bound***
Female participants					
Low	Medium	25.33	5.80**	12.97	37.70
	High	24.76	5.42***	13.22	36.31
Medium	High	-0.57	6.11	-13.59	12.45
Male participants					
Low	Medium	-2.38	4.78	-12.56	7.80

(A) Social agency	(B) Social agency	Mean differences (A-B)	*SE*	95% confidence interval for the difference	
				Lower bound	*Upper bound*
Female participants					
	High	-11.96	4.81*	-22.21	-1.72
Medium	High	-9.58	4.56*	-19.29	0.13

a. *SE* = standard error, ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Additionally, pairwise comparisons using Bonferroni correction showed a statistically significant difference in negative cognitions scores between male and female participants in the low social agency condition, $p < 0.001$. The score was 25.71 points higher for female participants than male participants, with 95% confidence interval [16.97, 36.46]. Pairwise comparisons using Bonferroni correction also showed a statistically significant difference in negative cognitions scores between male and female participants in the high social agency condition, $p = 0.05$. The score was 11.01 points higher for male participants than female participants, with 95% confidence interval [-0.07, 22.10].

On the other hand, there was no significant interaction effect of social agency and gender on feelings of anger, $F(2,15) = 1.01$, $p = 0.39$, partial $\eta^2 = 0.12$. Results also revealed no significant main effects of gender, $F(1,15) = 0.36$, $p = 0.56$, partial $\eta^2 = 0.02$ and no significant main effects of social agency, $F(2,15) = 0.66$, $p = 0.53$, partial $\eta^2 = 0.08$ on the feelings of anger. The mean score of feelings of anger for male participants increased as the robot was used as a persuasive agent compared to a text (low social agency: $M = 2.96$, $SD = 0.97$, medium social agency: $M = 3.13$, $SD = 0.99$ and high social agency: $M = 3.06$, $SD = 0.97$). Whereas for female participants, the feelings of anger score was lower when the persuasive messages conveyed by a robot (medium social agency: $M = 2.33$, $SD = 0.92$ and high social agency: $M = 2.75$, $SD = 0.89$) than a text (low social agency: $M = 2.92$, $SD = 0.88$).

Hypothesis 2: Compliance

An ANOVA test found no significant main effect of social agency on compliance, $F(2,54) = 0.34$, $p = 0.71$, partial $\eta^2 = 0.01$. To test whether social agency and gender of the participants effect compliance, an ANOVA analysis was run and the results found a) no significant interaction effect of social agency and gender on compliance, $F(2,54) = 1.16$, $p = 0.32$, partial $\eta^2 = 0.40$ b) a significant main effect of gender on compliance, $F(1,54) = 16.27$, $p < 0.001$, partial $\eta^2 = 0.23$ c) no significant main effect of social agency on compliance, $F(2,54) = 0.34$, $p = 0.71$, partial $\eta^2 = 0.01$ (see Figure 5.4).

Figure 3 shows that female participants ($M = 11.48$, $SD = 3.54$) complied more than male participants ($M = 7.67$, $SD = 03.51$) in all social agency conditions. Additionally, the difference of compliance score between male and female participants increased with higher social agency. However, no main effect of social agency on compliance was found for either female participants, $F(2,54) = 1.11$, $p = 0.34$, partial $\eta^2 = 0.04$ or male participants, $F(1,54) = 0.16$, $p = 0.85$, partial $\eta^2 = 0.01$. In terms of social agency, there was a statistically significant difference of compliance scores between male and female for participants who interacted with the agent displaying enhanced social cues in the high social agency condition, $F(1,54) = 12.45$, $p = 0.001$, partial $\eta^2 = 0.19$ and marginally significant at the medium social agency condition $F(1, 54) = 3.57$, $p = 0.06$, partial $\eta^2 = 0.06$. Pairwise comparison found significant differences of compliance for male and female participants in the high social agency condition using Bonferroni correction, $p < 0.05$. The score was 5.77 points, higher for female than for male participants, and the 95% confidence interval was [2.49, 9.05]. Additionally, the mean difference of compliance score was 3.21 points, and the 95% confidence interval was [-0.20, 6.63] higher for female than male participants in medium social agency condition also using Bonferroni correction. Nevertheless, the simple main effect of gender on compliance score for the participants in the low social agency condition was not significant, $F(1, 4) = 2.43$, $p = 0.13$, partial $\eta^2 = 0.04$.

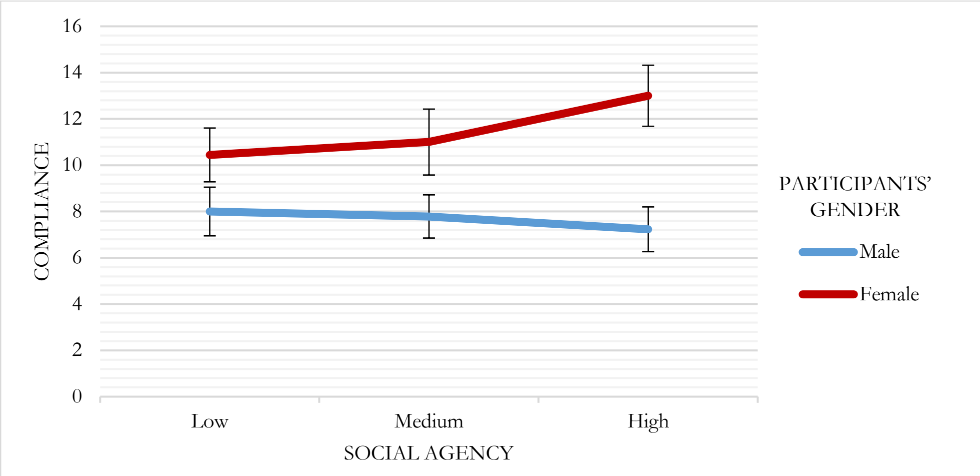

Figure 5.4: Mean and standard error of compliance scores by the social agency (low vs medium vs high) and gender of the participants (male vs female). Female participants demonstrated higher compliance compared to male participants. Results showed no main effect of social agency and no interaction effect between social agency and gender on compliance.

5.4 Discussion

This chapter provided a combined analysis of the data collected in the two experiments reported in Chapter 3 and Chapter 4. In Part 1 of the thesis, we have investigated how a persuasive agent influences decision-making task in a low psychological involvement issue by varying the level of social agency (persuasive-text vs robot with minimal cues vs robot with enhanced verbal and nonverbal cues). Following the Social Agency theory (Mayer et al., 2003), we expected that participants in our experiment would also show more social responses (psychological reactance and compliance) when presented with a persuasive agent that has stronger (or more) social cues.

According to our results, participants showed higher psychological reactance (especially negative cognitions) towards the robot in the high social agency condition compared to the robot in the medium social agency condition especially when the participants' gender was considered in the analysis. This impact of higher social agency did not hold for the comparison to a text-only condition; it is likely this was so because the very presence or not of the robot transforms the interaction in more ways than just the perception of the added social cues. That is, participants reading text focus on the text content, while in the presence of a robot, they share their attention between the robot and the text as reported in Chapter 3. Although there was no text condition in the manipulation of social agency reported in Chapter 4, the comparison of the text-only condition and the robot condition was ambiguous due to the different dimensionality of the social agency (text condition: 2D agent and robot condition: 3D agent). For this reason, the comparison of psychological reactance in the two social agency conditions involving the robot may be more reliable.

Our investigation on the phenomenon of psychological reactance supported recent reports that a robot with minimal social cues can elicit positive social responses in human-robot interaction. For example, an earlier study (Mutlu, Yamaoka, Kanda, Ishiguro, & Hagita, 2009) showed that gaze cues by a robot with mechanical face improves performance in a pair-game compared to playing with a robot with a human-like face. This could be because the interaction with a robot having a human-like face is cognitively and perceptually more demanding than the interaction with a simple mechanical-like robot (Mutlu et al., 2009). Also, Robins, Dautenhahn, and Dickerson (2009) found that a robot with minimal cues is adequate to encourage interactions between children with autism spectrum disorder and co-present adults in therapy sessions. Others like Tanis and Postmes (2003) have indicated that simple or minimal social cues are sufficient to reduce ambiguity and improve rapport in computer-mediated communication.

In our analysis, the highest psychological reactance was found in the low social agency condition (text only). This finding was unexpected since text has the least social cues of the three conditions so according to Social Agency theory (Mayer et al., 2003) we expected the lowest social responses; however, it provides supportive evidence for the value of robots in persuasion, since our participants felt less threatened when a robot persuaded them to change their selections compared to a simple persuasive text message. This finding contradicts earlier research (Roubroeks et al., 2011) which also concerned a task of low psychological involvement in persuasive attempts by similar social agencies as in the current study. It is known that people react differently to persuasive attempts, depending on their level of psychological involvement with the task at hand (Bell, 2016; Ligthart & Truong, 2015). To tease apart the impact of this phenomenon, further research should investigate the effect of psychological involvement on psychological reactance and compliance to robotic persuaders.

Our results suggested a significant interaction between social agency and gender on psychological reactance. Table 5.1 demonstrates the insignificant difference found in the psychological reactance in male and female participants in the medium social agency condition. On the other hand, psychological reactance scores for both low and high social agency conditions differed significantly for male and female participants. Additionally, Figure 5.2 shows that the participants reported the lowest psychological reactance, and had the least negative cognitions in the medium social agency condition (robot with minimal verbal and nonverbal cues). Interestingly, male and female participants experienced the persuasive messages delivered by the social agent in the low and high social agency conditions differently as illustrated in Figure 5.3. Females were more reactant to text while males were less reactant to it. On the other hand, when a robot with enhanced verbal and nonverbal cues (high social agency condition) delivered the persuasive messages, male participants reported that the robot was the most displeasing persuader. Then again, female participants found the robot to be a pleasing persuader and experienced lower psychological reactance to it.

This finding may have to do with the personality and physical appearance of the robotic persuader (a robot with masculine face and voice) as found in earlier research (Jung, Waddell, & Sundar, 2016). Although both the medium and the high social agency persuaders have the same physical appearance and provide the same advice, the highly social agent (with stronger social cues) was a stronger persuader in line with Social Agency theory (Mayer et al., 2003). It also appears that stereotypical gender patterns may have manifested themselves in the human-robot interaction as shown in earlier studies (Otterbacher & Talias, 2017; Tay, Jung, & Park, 2014). Depending on either a stereotypically male or a stereotypically female task while being instructed by either a 'male' or a 'female' robot, earlier study (Kuchenbrandt, Häring, Eichberg, Eyssel, & André, 2014) showed that gender typicality of the task significantly affected the collaboration with the robot in the context of a stereotypically female work domain. A potential explanation of our findings is that male participants perceived the persuasive messages from the male robot in the high social agency condition as a persuasive attempt by a competitor, stronger than the persuasive attempts by the medium social agent. Whereas, female participants may have reacted to the persuasive messages from the masculine robot in the high social agency condition as a persuasive attempt by a friend.

While this is a plausible explanation/conjecture, it has to be noted that our findings did not align with the similarity-attraction hypothesis (Byrne, 1971; Byrne & Nelson, 1965). Although our results did not find the expected influence of social agency on compliance, we found a significant effect of gender on compliance, in which female participants complied more than male participants (see Figure 5.4). Specifically, female participants amicably agreed to change their final choices most of the time as suggested by the robot (both in the medium and in the high social agency conditions). On the contrary, male participants ignored most of the persuasive messages given by the robot in the high social agency. Thus, in parallel to the assumption of social agency and the gender effect on psychological reactance found in this analysis, we believe that female participants felt at ease (low psychological reactance) to follow the advice given by the male robot, which later influenced their decision to change their choices and comply with the persuasive messages.

5.5 Summary

This chapter indicates the potential added value of using a robot as a persuasive agent. To conclude Part 1, we have learned that a persuasive robot displaying minimal verbal and nonverbal social cues (neutral facial expression, blinking eyes) during persuasive attempts can reduce the psychological reactance than the robot with more enhanced social cues (emotional intonation voice, head movement, and facial expression). Another crucial finding emerging from this chapter that warrants further investigation pertains the characteristics of social cues which is gender of the robot and the users; our analysis provided preliminary evidence that a robotic agent of the opposite gender may lead to lower psychological reactance than a robot of the same gender. Consequently in Part 2 of the thesis, we explore the effect of characteristics of social cues for persuasive robots on psychological reactance, compliance and other social responses such as trusting beliefs and liking.

PART II

CHARACTERISTICS OF SOCIAL CUES

In this part, we investigate the characteristics of social cues for persuasive robots on social responses. In Chapter 6, we present the design of non-interactive social cues for persuasive robots: its facial characteristics and gender similarity with the users on psychological reactance, compliance and trusting beliefs. In Chapter 7, we present the design of interactive social cues for persuasive robots: head mimicry and interactive social praises on psychological reactance, compliance, trusting beliefs and liking. We aim to explore the desirable characteristics of social cues for persuasive robots so that the persuasive attempts will be effective (high compliance) and positively perceived (low psychological reactance, high trusting beliefs and high liking) by humans.

CHAPTER 6

Investigating Non-Interactive Social Cues: Trustworthy Facial Characteristics and Similar Gender with Users Elicit

This chapter is based on a published paper:

Effects of robot facial characteristics and gender in persuasive human-robot interaction (2018). *Frontiers in Robotics and AI, 5*(73). DOI: 10.3389/frobt.2018.00073

The studies reported in Part 1 showed that people experience lower psychological reactance when interacting with a robot that displays minimal social cues than a robot that displays enhanced social cues. Relatedly, we found that high coerciveness language causes higher compliance, while high psychological involvement game causes lower compliance and higher psychological reactance. The growing interest in social robotics makes it relevant to further examine how robot characteristics influence the way people experience such interactions and comply with the persuasive attempts by robots. Other than psychological reactance and compliance, we add trusting beliefs as a social response measure in this chapter. The purpose of this chapter is to identify how the ostensible gender and the facial characteristics of a robot influence the psychological reactance experienced by people and the extent to which they trust the robot during its persuasive attempts. This chapter reports a laboratory study where SociBot displayed different faces and gender as social cues, while delivering persuasive messages to participants playing a trust game. Results showed that a robotic advisor with upturned eyebrows and lips (features that people tend to trust more in humans) is more persuasive, evokes more trust and less psychological reactance compared to one displaying eyebrows pointing down and lips curled downwards at the edges (facial characteristics typically not trusted in humans). The gender of the robot did not affect trust, but participants experienced higher psychological reactance when interacting with a robot of the opposite gender. Remarkably, mediation analysis showed that liking of the robot fully mediates the influence of facial characteristics on trusting beliefs and psychological reactance. Also, psychological reactance was a strong and reliable predictor of trusting beliefs but not of compliance.

6.1 Introduction

Similar to human-human relationships, evidence suggests that trust in the robotic interaction partner is crucial for developing human-robot relationships. Humans should feel safe to rely on social robots for physical or even emotional support (Rotter, 1967). Earlier research (Hancock et al., 2011) suggested that robot-related factors (such as the robot's performance), human-related factors (like personality traits of the human) and environmental factors (for instance the complexity of the task assigned) are crucial for developing trust in human-robot interaction. A meta-analysis by Hancock et al. (2011) concluded that robot characteristics are also instrumental in developing trust for human-robot interaction. Social Agency theory (Mayer et al., 2003) stipulates that adding human features as social cues on the robot like facial expression, voice, and physical presentation could enhance the chance for a human to perceive the technology more positively. This hypothesis was supported by findings in several studies (Andrist, Spannan, & Mutlu, 2013; Cooney et al., 2015; Edwards et al., 2018; Eyssel & Hegel, 2012; Moro, Lin, Nejat, & Mihailidis, 2018).

There have been a few attempts to endow robots with human-like features so that humans will find it easier to trust them. These include matching human likeness (Mathur & Reichling, 2016), behaviour (Goetz, Kiesler, & Powers, 2003), head movement and facial characteristics like gaze and eyelid movements (Lee & Breazeal, 2010), and gestures (Moro et al., 2018; Tang, Charalambous, Webb, & Fletcher, 2014). An earlier study (Verberne, Ham, & Midden, 2015) showed that a significant characteristic that influences user trust is the similarity (looks, acts, and thinks) between the user and an artificial agent (Siegel et al., 2009) as suggested by similarity-attraction hypothesis (Byrne, 1971). This research (Verberne, Ham, & Midden, 2015) used the trust game concept (see also de Vries (2004)) to measure trust that the participants have in their (artificial) interaction partner. In this trust game, participants can allocated resources to their (artificial) interaction partner, which the game will double if the interaction partner collaborates, thereby giving a quite direct, behavioral measure of trust in that interaction partner.

A salient characteristic that also can be similar to the user is the robot's ostensible gender (for brevity we refer to it simply as gender in the remainder of this chapter). To date, only a few studies have investigated how the robot's gender influences trust and these studies have produced mixed results (Crowelly, Villanoy, Scheutzz, & Schermerhornz, 2009; Eyssel & Hegel, 2012; Eyssel, Kuchenbrandt, Bobinger, de Ruiter, & Hegel, 2012; Powers et al., 2005; Siegel et al., 2009). Some earlier studies suggested that similarity between a robot's and a user (Verberne, 2015) especially similarity in terms of gender (Eyssel & Hegel, 2012) might increase the user's trust. Another experimental study (see Siegel et al. (2009)) found that both men and women trust robots of the opposite gender more than robots of the same gender.

Robotics researchers have examined several approaches to encourage the attribution of gender to a robot so that people would perceive it more positively. For instance, male robots were given short hair and female robots long hair in evaluating gender-stereotyping tasks like monitoring technical devices and childcare (Eyssel & Hegel, 2012). Other research (Siegel et al., 2009) used robots with pre-recorded masculine or feminine voices in donation tasks, or utilized a conversational robot that had grey vs. pink lips in discussions about dating norms (Powers et al., 2005). In a between subjects design study, (Crowelly et al., 2009) used synthetic voices (male vs. female voices) and gender-specific names ("Rudy" for male robots vs. "Mary" for female robots) to manipulate user perceptions of a robot gender. Based on the outcomes and research methodology developed in earlier studies (Alexander, Bank Yang, Hayes, & Scassellati, 2014; Eyssel & Hegel, 2012; Jung et al., 2016; Siegel et al., 2009; Verberne, Ham, & Midden, 2015), this study reported an experiment that examines the influence of the robot's gender on trust.

Trust towards the robot may also be influenced by its facial characteristics. It is well known that humans make social judgments about other people's faces and similar reactions have been observed towards artificial agents. Earlier research suggested that the level of trust towards a social agent depends on various aspects, for example, its level of embodiment (robot, avatar or a picture) (Rae, Takayama, & Mutlu, 2013), its ability to display social cues (Ruhland et al., 2015; Xin, Liu, Yang, & Zhang, 2016), and its appearance (Złotowski et al., 2016). An earlier research (Mathur & Reichling, 2016) found that the trustworthiness of a robot varied with the likeness of the robot's face to a human following a general pattern known as the 'uncanny valley' (see Mori (1970)): trustworthiness, in this case, did not increase linearly with human likeness but dropped when the agent was very realistic but not yet perfectly human-like.

A series of studies by Todorov and colleagues (Todorov, Baron, & Oosterhof, 2008; Todorov, Olivola, Dotsch, & Mende-Siedlecki, 2015; Todorov & Oosterhof, 2011) examined how facial characteristics of a social agent can influence user's trust. They generated pictures of unfamiliar faces to display facial characteristics representing three levels of trust: most trustworthy, neutral, and least trustworthy (Todorov & Oosterhof, 2011). The generation of facial characteristics was evaluated on the basis of functional Magnetic Resonance Imaging (fMRI) of participants. These studies (Todorov et al., 2008; Todorov et al., 2015) concluded that humans perceived upturned eyebrows and lips as the most trustworthy facial characteristic, while the least trustworthy face was the one with eyebrows pointing down and lips curled down at the edges. However, these results are still tentative, since facial characteristics were only represented in 2-dimensional images, and have not yet been tested with an embodied agent or a robot. In addition, scholars like Vidotto, Massidda, Noventa, and Vicentini (2012) as well as McKnight et al. (1998) remarked that there were different conceptions of trust towards interaction partners such as trusting beliefs and trusting behaviours (we call trusting behaviours as compliance in this thesis). However, Todorov et al. (2008) did not specify which type of trust was generated from manipulating these facial characteristics. Furthermore, Todorov et al. (2008) only assessed first impressions towards the appearance of those characters and their study participants did not interact with the characters.

As people respond to social cues (Atkinson et al., 2005; Lee, Breazeal, & DeSteno, 2017) from technologies (Reeves & Nass, 1996) as shown in previous chapters of the thesis, we anticipated that participants in this study will also show some social responses towards the social robot. Therefore in this study, we reported an experiment that examined the influence of gender similarity between humans and robots (similar vs. opposite genders) as well as the facial characteristics of the robot (least vs. most trustworthy). The social responses under study include users' psychological reactance towards the interaction, compliance and trusting beliefs in the robot. Based on earlier research, we expected that gender similarity (Verberne et al., 2015) and the most trustworthy facial characteristics (Todorov et al., 2015; Todorov & Oosterhof, 2011) will evoke higher trust towards the robot. However, we did not predict how similarity in gender and facial characteristics affects psychological reactance, which has not yet been examined by earlier research. Additionally, we predicted that higher psychological reactance (caused by perceived loss of freedom) causes lower trust, as reported by Dowd, Pepper, and Seibel (2001), Lee et al., 2014 as well as Sue et al. (1998) in separate studies.

The Current Study

We examined the influence of gender similarity (similar vs. opposite) between a robot and a human upon psychological reactance, compliance and trusting beliefs the humans feel towards the robot in this chapter. We also examined whether facial characteristics engender trust in line with how Todorov et al. (2008) found that people judge trustworthiness from photos. Besides, this chapter also investigated how psychological reactance towards a robotic persuader can influence trust. Trust was measured in terms of compliance and trusting beliefs. Participants played a trust game inspired by the investment game (Berg, Dickhaut, & McCabe, 1995; Xin et al., 2016) and the route planner game concept (de Vries, 2004), in which they were asked to make a drink for an alien as in earlier chapters.

More specifically, in this study, participants could decide between letting the robot choose the ingredients for the drink, thus exhibiting a compliance towards the choice made by the robot (Vidotto et al., 2012), or selecting their own ingredients and thus demonstrating distrusting behaviour (or incompliance) towards the robot. Facial characteristics and gender were implemented in SociBot as shown in Figure 6.1.

The general task of the interaction was that the participant should create a beverage for an alien, which involves several choices for the ingredients as in earlier chapters. While making these choices, the robot served as an advisor, assisting the participants in making their decision in selecting the ingredients for the beverage upon request. The hypotheses were presented in four parts, pertaining to psychological reactance, compliance and trusting beliefs:

H1. Psychological reactance

H1(a). There is a significant difference in psychological reactance score between participants interacting with robot with the most trustworthy face and those interacting with the one with the least trustworthy face

H1(b). There is a significant difference in psychological reactance score between participants interacting with a robot of the same gender and participants interacting with a robot of the opposite gender

H2. Compliance

H2(a). There is a significant difference in compliance score (requesting more help) between participants interacting with a robot with the most trustworthy face and those interacting with a robot with the least trustworthy face

H2(b). There is a significant difference in compliance score (requesting more help) between participants interacting with a robot with the same gender and those interacting with a robot with the opposite gender

H3. Trusting beliefs

H3(a). There is a significant difference in trusting beliefs score between participants interacting the robot with the most trustworthy face and those interacting with the robot with the least trustworthy face

H3(b). There is a significant difference in trusting beliefs score between participants interacting with a robot of the same gender and those interacting with a robot of the opposite gender

H4. Correlation between psychological reactance, compliance and trusting beliefs

Psychological reactance has a strong significant correlation to compliance and trusting beliefs

6.2 Materials and Methods

6.2.1 Participants and Design

Seventy-two adult participants (41 males and 31 females) were recruited; with ages ranging between 18 and 47 (M = 23.90, SD = 4.15). Participants played a game with the SociBot which offered them persuasive advice and displayed different facial characteristics and gender according to the experimental condition. The experiment followed a 2x2 between-subjects design with facial characteristics (the most trustworthy face vs. the least trustworthy face) and gender similarity (similar vs. opposite) as independent variables. Participants were given a reward for participation (€7.5 for university students and €9.5 for external participants) and a different type of chocolate bar as a reward based on the participant's score during the game.

6.2.2 Manipulations

Manipulation of Facial Characteristics

During the experimental session, half of the participants played with the robot advisor that showed eyebrows pointing down and lips curled downwards at the edges: the least trustworthy facial characteristics according to earlier studies (Todorov et al., 2008; Todorov et al., 2015). More specifically, based on Facial Action Coding System (FACS), facial characteristics that were altered (from the neutral face of the robotic advisor) were inner brow raiser, outer brow raiser, lips toward each other, upper lip raise, lip corner puller, dimpler, and lip pucker. The remaining participants played with SociBot featuring a face which was labelled as the trustworthy advisor with upturned eyebrows and lips. For the least trustworthy face, facial characteristics that differ from neutral face were: nasolabial deepener, lip corner depressor, lips toward each other, lip pucker, and lid tightener (Ekman & Friesen, 1976).

Both groups started the session by first interacting with the robot as a demonstrator. The demonstrator had the same gender as the participant and displayed neutral face and expression (refer to Figure 6.1 for more graphical details of the facial images) in order to establish a baseline context of the agent's facial characteristics and gender. Baseline conditions using neutral face were commonly used in earlier research (Kohler, Walker, Martin, Healey, & Moberg, 2009; Stuhrmann, Suslow, & Dannlowski, 2011). This step was taken to allow controlling for individual differences in trusting somebody (in this case the robotic advisor).

These facial characteristics (demonstrator and advisor's faces) were embedded into one robot only. The advisor (both with least trustworthy and most trustworthy faces) as well as the demonstrator resembled a human with light brown skin colour tone and hazel eyes as used in the previous chapters.

Manipulation of Gender Similarity

Two types of robot's gender were used in this study, which was the same (similar) or the opposite (opposite) gender of the advisor versus the participant. The participants were asked to self-identify their gender as part of a demographic questionnaire, and the information given was 100% the same as the experimenter's observation. For participants in the similar gender condition, the advisor was given an identity as male (face and voice) if the participant identified himself as male while a female advisor was used if the participant is female. In contrast, the advisor's gender would be opposite to the participant's gender in the opposite gender condition. The gender for the demonstrator was always the same gender as the participant.

6.2.3 Task

For this chapter, we adapted the 'Beverages Creation Station' game used in earlier chapters by following the trust game concept (Berg et al., 1995; de Vries, 2004). We also made an adaptations in our developed game by adding a 'credit' display to the GUI of the game and an option for asking the robot to make a choice as shown in Figure 6.2.

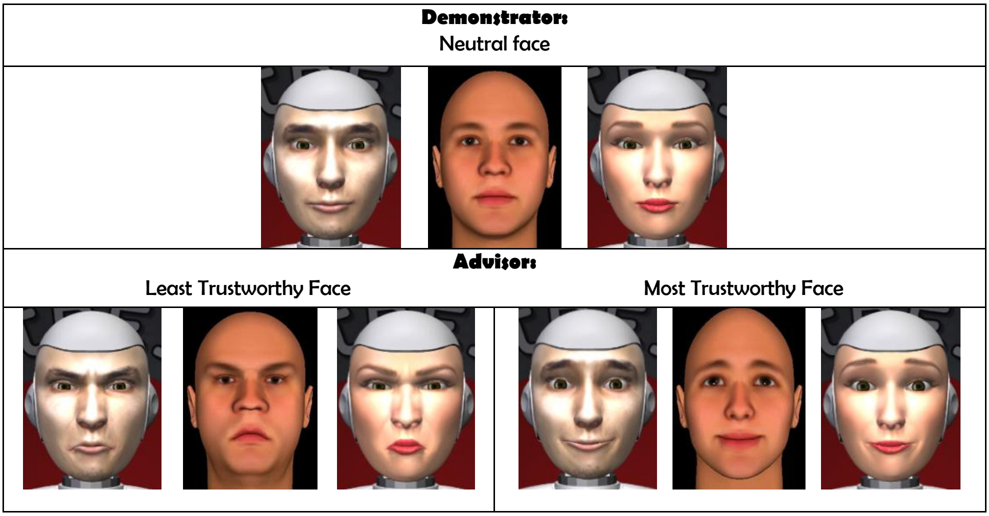

Figure 6.1: Facial characteristics of the demonstrator and the two advisors. For each case, there are corresponding: male robot (left), images from the study of (Todorov and Oosterhof, 2011) (center) and female robot (right).

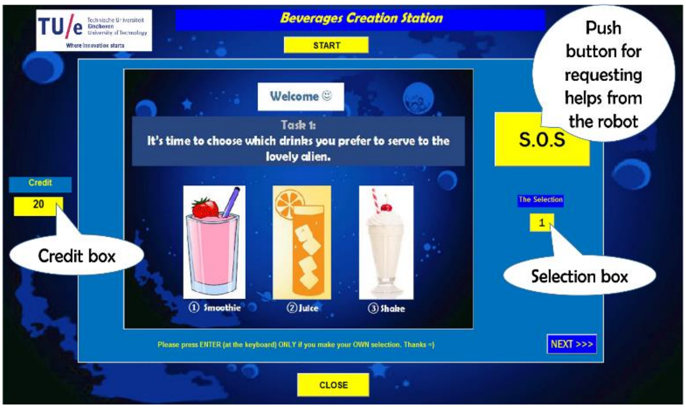

Figure 6.2: GUI of the trust game.

The trust game was implemented as follows: Each participants was given 20 credits at the start of the game. Every move costs one credit, but if the participant asks the robot to make selection, it costs 2 credits. Participants win 4 credits for every correct choice they make. Participants are only informed what the right choices after the end of the game.

The robot used highly coercive language based on the findings presented in Chapter 3 which we found that forceful language in persuasion activity by robot leads to higher compliance e.g. *'You are obliged to pick the third design'* and *'Definitely, choose honey!'*

6.2.4 Procedure

Participants sat on a chair facing the robot. A laptop that was placed in front of the participants was used to fill in questionnaires and play the game (see Figure 6.3). An IP camera attached to the laptop screen recorded participants' facial expression while playing the game. The experiment consists of three phases: 1) Introduction [5 minutes] 2) Demonstration [10 minutes] 3) Experiment [30 minutes].

In the first phase, participants gave informed consent and demographic information, and the experimenter summarized the experimental procedure.

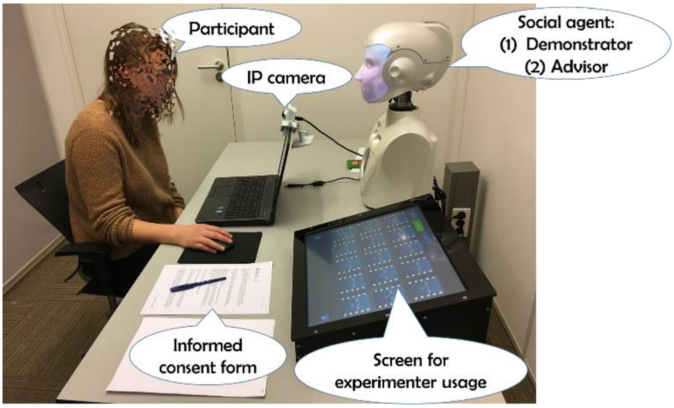

Figure 6.3: Experimental set ups.

In the second phase, the experimenter introduced the first robotic character called the 'demonstrator' and demonstrated how to play the game. Before the experimenter would leave the room, the participant was reminded that the robot was on the same team as the participant and had the responsibility to help the participant achieve the highest score possible. The experimenter also reminded the participant that it is up to them whether to trust the advisor in the selection process. Then, the participant could fill in a questionnaire consisting of evaluative questions regarding their impression of the demonstrator.

In the third phase, the participant played the game. During this phase, the robot would assume the character of the advisor. The advisor greeted the participant by introducing itself as 'Hello, I am your advisor' to make the participant aware of the changed role of the agent. After making all selection tasks, the second questionnaire appeared on the screen as a Google form labelled as the 'Advisor Questionnaire' in which, the participants were asked to evaluate their experience of playing the game together with the advisor.

6.2.5 Measures

Psychological Reactance

Based on the Intertwined Model of Reactance (Dillard & Shen, 2005; Rains & Turner, 2007), we took two measures of psychological reactance based on self-report: feelings of anger and negative cognitions as in earlier chapters.

Additionally, the facial emotional expression of the participants while interacting with the advisor were captured and analyzed using a software called FaceReader (Adams Jr, Garrido, Albohn, Hess, & Kleck, 2016; Barakova, Gorbunov, & Rauterberg, 2015) which is based on Facial Action Coding System (FACS) (Ekman & Friesen, 1976). We counted the instances where FaceReader would classify a facial expression as angry to obtain a behavioural measure of psychological reactance.

A reliability analysis on the proposed psychological reactance elements: feelings of anger, negative cognitions, and facial emotion (anger as detected by the FaceReader software) showed that the Cronbach's *a* increased by eliminating the measurement based on the facial expression of emotion. Therefore, we constructed a reliable (Cronbach's *a* = 0.89) measure of psychological reactance by taking into account the user's scores on feelings of anger and negative cognitions only.

Compliance

The game affords a clear compliance measure, namely how many times participants ask the help of the advisor to make selections on behalf of themselves. For example, if a particular participant would ask the designated advisor to make selection only for tasks 1, 5, 6, and 8 while answering the remaining six tasks independently, then he/she would be given the compliance score of 4.

Trusting beliefs

We measured trusting beliefs with a questionnaire using the scale developed by Jian, Bisantz, and Drury (2000), perceived trust by using a scale by Tay et al. (2014) and a scale by Heerink, Krose, Evers, and Wielinga (2009), as well as individualized trust evaluations by using a scale developed by Wheeless and Grotz (1977). We combined the overlapping questions as appropriate. For example, both trust scale items (Jian et al., 2000) and the individual trust scale (Wheeless and Grotz, 1977) ask how much a participant thinks the advisor is honest. The combined trusting beliefs questionnaire includes two sets of items:

(i) The Likert scale of 7 levels ranging from completely disagree to completely agree toward the following statements: (from trust scale items questionnaire by Jian et al. (2000)) *The advisor behaves in an ethical manner, I am confident of the intentions, actions, and outputs of advisor, I am not wary of the advisor, I am confident with the advisor.* Another three Likert scales of 7 levels inquired agreement with statements that were adapted from the perceived trust questionnaires (Heerink et al., 2009; Tay et al., 2014) including: *I will trust the advisor if the advisor gives me advice again in the future, I trust that the advisor can provide me correct answers to the game*, and *I will follow the advice that the advisor gives me.*

(ii) Nine semantic differential items with seven levels adapted from the individualized trust scale questionnaire (Wheeless and Grotz, 1977) with the following poles: *untrustworthy-trustworthy, unreliable-reliable, insincere-sincere, dishonest-honest, distrustful-trustful, inconsiderate-considerate, divulging-confidential, deceitful-not deceitful*, and *disrespectful-respectful.*

A reliability analysis showed that the various components of our combined trusting beliefs questionnaire were highly correlated. By combining all the questionnaire items (described above), we were able to construct a highly reliable (Cronbach's α = 0.96; 16 items) trusting beliefs measure.

Exploratory Measures

A number of extra measures were taken to support exploratory analysis: a semantic differential scale with endpoints masculine/feminine, and 7-point scales to rate the following properties: healthy, and attractive (Verberne et al., 2015).

To measure how much participants liked the designated advisor, we used the partner liking rate scale by (Guadagno & Cialdini, 2002) which includes thirteen 7-point Likert scales assessing partners by the following characteristics: *approachable, confident, likeable, trustworthy, interesting, friendly, sincere, warm, competent, informed, credible, modest* and *honest*.

The degree of anthropomorphism and perceived intelligence of the advisor were rated using 5-point semantic differentials from the Goodspeed Questionnaire (Bartneck et al., 2009) indicating that *'The advisor was': fake/natural, machinelike/human-like, unconscious/conscious, artificial/lifelike* and *moving rigidly/moving elegantly* for anthropomorphism factor; whereas *incompetent/competent, ignorant/knowledgeable, irresponsible/responsible, unintelligent/intelligent,* and *foolish/sensible* for perceived intelligence.

6.3 Findings

6.3.1 Manipulation Check

An examination of participant's perception of advisor's gender revealed the main effect of our masculinity/ feminine manipulation, $F(1, 70) = 1317.8$, $p < 0.001$ using one-way Analysis of Variance (ANOVA) test. A Brown-Forsythe test of equality of means revealed a significant relationship between the perception of advisor's gender (feminine vs. masculine) and the advisor's gender, $F(1, 64.71) = 1601.86$, $p < 0.001$, which means that the gender of the robot was perceived correctly by all participants. In addition, the female advisor was perceived as more feminine ($M = 6.07$, $SD = 0.83$, $n = 30$) than the male advisor perceived as masculine ($M = 5.50$ $SD = 1.60$, $n = 42$).

6.3.2 Hypothesis Testing

We conducted statistical analyses for testing the experimental hypotheses after ensuring that the conditions and assumptions for the tests (e.g., ANCOVA etc.) were met.

Hypothesis 1: Psychological Reactance

<u>Hypothesis 1(a)</u>

To test whether facial characteristics influence psychological reactance, we conducted a repeated measures Analysis of Covariance (ANCOVA) test after ensuring that all conditions and assumptions for this test were met (e.g., we found no evidence for multicollinearity, extreme outliers, or non-normal distribution).

Facial characteristics were used as the independent variables, psychological reactance (measured by feelings of anger and negative cognitions) as the dependent variable, and psychological reactance evaluations in the demonstration session (feelings of anger and negative cognitions towards demonstrator) as the covariate. Result demonstrated a significant main effect of facial characteristics on psychological reactance, $F(1, 68) = 22.94$, $p < 0.001$. The lowest psychological reactance recorded by the participants in the most trustworthy face condition (*M* = 1.07, *SD* = 0.72) and the highest reactance experienced by the participants who interacted with the least trustworthy faced advisor (*M* = 1.91, *SD* = 0.72) (see Figure 6.4).

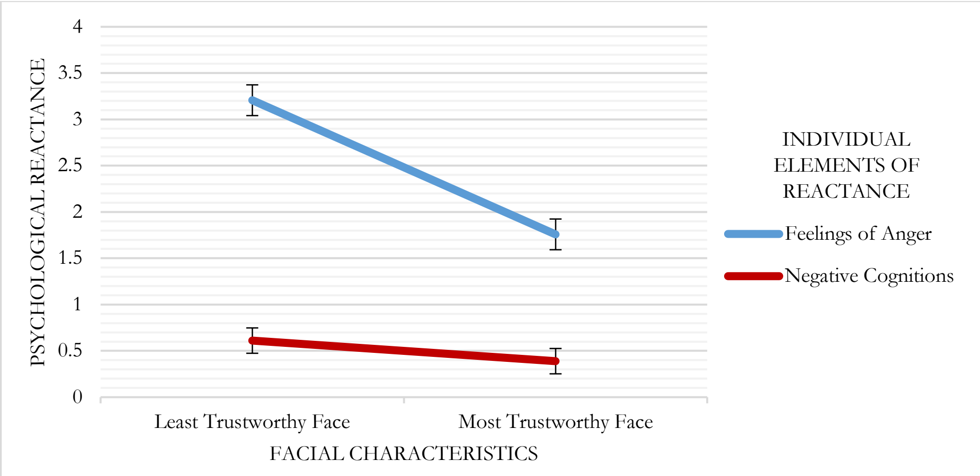

Figure 6.4: Mean and standard error of psychological reactance elements (feelings of anger and negative cognitions) scores by facial characteristics (least trustworthy face vs. most trustworthy face). Participants reported lower psychological reactance (and significantly lower feelings of anger) when interacting with the most trustworthy face advisor than the least trustworthy face advisor. Results showed no significant main effect of facial characteristics on negative cognitions.

Two separate ANCOVAs were employed to investigate the influence of facial characteristics on the components of reactance: feelings of anger (the first ANCOVA) and negative cognitions (the second ANCOVA). For the first ANCOVA, the facial characteristics manipulation resulted a significant main effect for feelings of anger towards the advisor (with feelings of anger towards demonstrator as a covariate), $F(1, 69) = 38.25$, $p < 0.001$, partial $\eta^2 = 0.36$. However for the second ANCOVA, no significant main influence of facial characteristics was found on negative cognitions score (with negative cognitions towards demonstrator as a covariate), $F(1, 69) = 1.34$, $p = 0.25$, partial $\eta^2 = 0.02$. The mean difference of feelings of anger score for the least trustworthy face advisor and the most trustworthy face advisor was 1.46 points (with a 95% confidence interval [0.99, 1.93]) higher for the least trustworthy face advisor than for the most trustworthy face advisor.

<u>Hypothesis 1(b)</u>

The second hypothesis for psychological reactance predicted that participants who interacted with an advisor of a similar gender would experience significantly difference level of psychological reactance compared to the participants in the opposite gender condition. To test this hypothesis, the psychological reactance score for the advisor (feelings of anger and negative cognitions) was submitted to gender similarity (similar vs. opposite) x 2 (repeated measure of feelings of anger and negative cognitions towards advisor) x 2 (repeated measure of feelings of anger and negative cognitions for demonstrator as covariates) in ANCOVA test. There was no significant main effect of gender similarity on psychological reactance, $F(1, 68) = 0.07$, $p = 0.80$.

Overall, not supporting our hypothesis, results provided no evidence that the participants who interacted with similar gender's advisor (M = 1.47, SD = 0.14) experienced lower or higher psychological reactance than the participants who interacted with opposite gender's advisor (M = 1.52, SD = 0.14). However, results also showed that the effect of gender similarity on psychological reactance was different for the two components of psychological reactance, indicated by an interaction of gender similarity and psychological reactance component (repeated measure of feelings of anger and negative cognitions towards advisor), $F(1, 68) = 4.70$, $p = 0.08$. Further explorations of the relationship between the dependent and independent variables in verifying this hypothesis are elaborated in Table 6.1 by separating the psychological reactance component into individual measures of feelings of anger and negative cognitions.

Table 6.1: Mean scores on psychological reactance elements (and standard deviations between brackets) for the gender similarity manipulation.

Gender similarity	**Psychological reactance**	
	Feelings of anger	***Negative cognitions***
Similar	2.64 (1.07)	0.31 (0.52)
Opposite	2.33 (1.38)	0.69 (1.01)

Simple effect analyses showed that there was no statistical significant difference of gender similarity on feelings of anger, $F(1, 69) = 0.96$, $p = 0.33$, partial $\eta^2 = 0.01$. Still, the influence of gender similarity was significant on negative cognitions, $F(1, 69) = 4.10$, $p = 0.05$, partial $\eta^2 = 0.06$. That is, results provided no evidence that when participants interacted with the advisor that has similar gender to them, the feelings of anger (M = 2.64, SD = 1.08) were higher or lower compared to the participants in opposite gender interactions (M = 2.33, SD = 1.38). In contrast, the negative cognitions for the participants in the similar gender conditions (M = 0.31, SD = 0.52) was lower than the participants in opposite gender conditions (M = 0.69, SD = 1.01).

A repeated measure ANCOVA test was run with participants' and advisor's genders as independent variables, psychological reactance towards advisor as a dependent variable, and psychological reactance towards demonstrator as a covariate. Result revealed no significant interaction effect between those variables, $F(1,66) = 0.01$, $p = 0.94$, partial η^2=0.07 as demonstrated in Figure 6.5.

Figure 6.5 shows that male participants (M = 1.43, SD = 0.82) always recorded the lowest psychological reactance compared to female participants (M = 1.57, SD = 0.87) in regards to the advisor's gender. Besides, it can also be concluded that female advisor (M = 1.55, SD = 0.83) provoked higher psychological reactance to occur during the interaction compared to male advisor (M = 1.44, SD = 0.85). More importantly, male participants experienced higher psychological reactance when interacting with the opposite gender advisor: with female advisor (M = 1.49, SD = 0.99) and with male advisor (M = 1.38, SD = 0.69). However, the psychological reactance score for female participants was lower when they were interacted with opposite gender advisor. That is, male advisor (M = 1.53, SD = 1.04) and female advisor (M = 1.63, SD = 0.58).

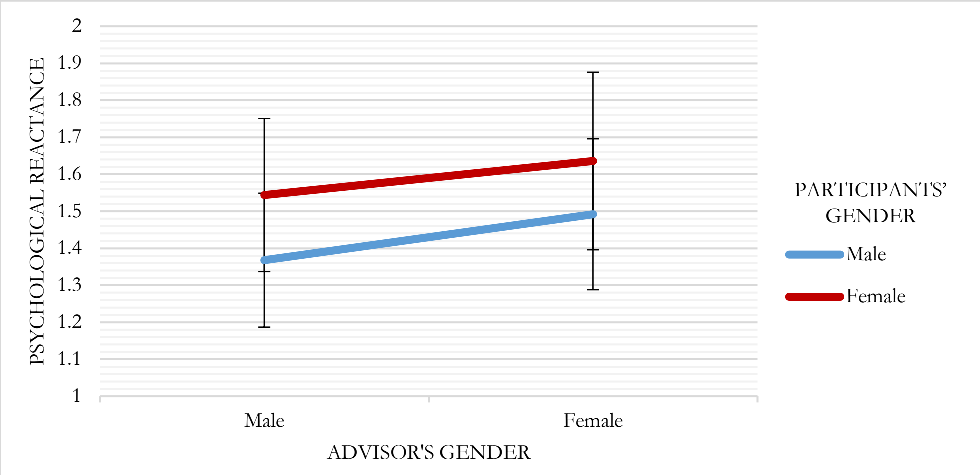

Figure 6.5: Mean and standard error of psychological reactance scores by advisor's gender (male vs. female) and participants' gender (male vs. female). Overall, participants that interacted with similar gender advisor (e.g. male participants paired with male advisor) reported lower psychological reactance, especially negative cognitions compared to opposite gender advisor (e.g. male participants paired with female advisor).

In summary, the main finding from this analysis is that psychological reactance (especially negative cognitions) was lower when the robot has a similar gender to the human persuadee. Further, psychological reactance (especially feelings of anger) was lower when the robot featured trustworthy facial characteristics.

Trust

In this chapter, we intended to combine trusting beliefs and trusting behaviours (discussed so far as compliance in this thesis) components into one measurement that we named trust. A Pearson correlation test was run to check if there is a correlation between these two measurements and also to check the strength of the correlation. As a result, we found that there was no significant (*n.s*) correlation between the two components, r = 0.15, p = 0.20. Based on this outcome, the trust measure was split into two different hypotheses: compliance and trusting beliefs.

Hypothesis 2: Compliance

Hypothesis 2(a)

The analysis of the compliance scores revealed a main effect of the facial characteristics manipulation, $F(1, 70) = 4.12$, $p = 0.05$, partial $\eta^2 = 0.06$ using one-way ANOVA test. On average, participants showed higher compliance towards an advisor with the most trustworthy face, M = 5.31, SD = 2.41 than towards an advisor with the least trustworthy face, M = 4.25, SD = 1.98. Overall (almost in all tasks), participants preferred asking the advisor to solve the tasks more often when the robot advisor they interacted with displayed the most trustworthy face rather than the least trustworthy face.

Hypothesis 2(b)

To test whether gender similarity significantly influence compliance, two separate Multivariate Analysis of Variance (MANOVA) analyses were run and the results found a) no significant main effects of gender similarity, $F(1, 70) = 0.10$, $p = 0.76$, partial $\eta^2 = 0.001$, and b) no interaction effect of the manipulations of participants' gender and advisor's gender on trusting behaviours score, $F(1, 68) = 0.29$, $p = 0.59$, partial $\eta^2 = 0.004$ (see Figure 6.6).

Figure 6.6 suggests that the female advisor induced higher compliance ($M = 5.03$, $SD = 2.50$) than the male advisor ($M = 4.59$, $SD = 2.06$) independent of the participants' gender. Further statistical exploration was done to investigate whether either male or female participants tend to show higher compliance towards the advisor (by neglecting the advisor's gender). It can be seen from the graph in Figure 6.6 that female participants ($M = 5.00$, $SD = 2.45$) complied with the robotic advisor more than the male participants ($M = 4.61$, $SD = 2.11$).

In summary, these results suggested that people showed more compliance towards a robot displaying facial characteristics they trust on humans, which did not seem to be affected gender similarity, while there was some evidence that they appeared to show higher compliance to a female robot more than a male robot.

Hypothesis 3: Trusting Beliefs

Hypothesis 3(a)

The result from Univariate Analysis of Covariance (ANCOVA) is consistent with *H2(a)* which predicted that the advisor with the most trustworthy facial characteristics (i.e. with eyebrows pointing down and lips curled at the edges) would attain higher trusting beliefs than the least trustworthy face's advisor. By using the trusting beliefs score on demonstrator as a covariate, a significant difference was found ($F(1, 69) = 16.61$, $p < 0.001$, partial $\eta^2 = 0.19$) between the trustworthiness of the advisor with the most trustworthy facial characteristics ($M = 5.29$, $SD = 0.88$) and the advisor with the least trustworthy facial characteristics ($M = 4.38$, $SD = 1.04$).

Hypothesis 3(b)

An ANCOVA found no main effect of gender similarity (between the advisor and participants) on trusting beliefs, $F(1, 69) = 0.001$, $p = 0.98$ (*n.s.*) for which hypothesis *H3(b)* is rejected. Thus having similar or opposite gender did not lead to reporting different trusting beliefs (see Table 6.2).

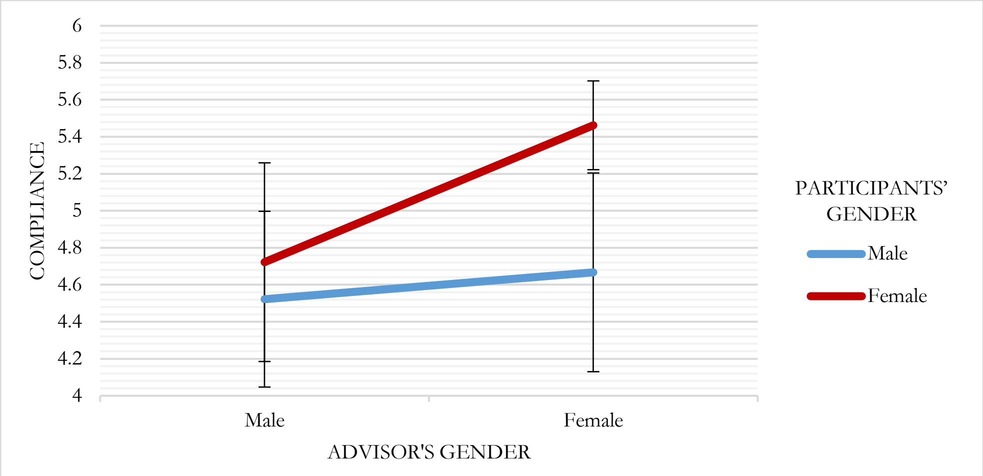

Figure 6.6: Mean and standard error of compliance scores by advisor's gender (male vs. female) and participants' gender (male vs. female). Participants (independent of their gender) reported higher compliance about the female advisor (vs. male advisor). Female participants reported higher compliance about an advisor (independent of the advisor's gender) than male participants.

Table 6.2: Mean scores on trusting beliefs (and standard deviations between brackets) for the gender similarity manipulation.

Advisor's Gender	**Participants' Gender**	***Mean* (*SD*)**	***N***
Male	Male	5.06 (0.58)	23
	Female	4.68 (1.24)	18
Female	Male	4.97 (1.26)	18
	Female	4.43 (1.10)	13

When disentangling gender similarity into its components of participants' gender and advisor's gender, results (as shown in Table 6.2) showed that male participants reported slightly higher trusting beliefs toward the advisor (M = 5.02, SD = 0.92) (independent of the advisor's gender or the facial characteristics of the advisor) as compared to the female participants (M = 4.57, SD = 1.17). Presenting evidence for this difference, an ANCOVA using facial characteristics and participants' gender as independent variables, the trusting beliefs score towards the advisor as the dependent variable, and postulated the trusting beliefs score towards the demonstrator as a covariate, showed a main effect of participants' gender, $F(1, 67) = 6.38$, $p = 0.01$, partial $\eta^2 = 0.09$. Gender of the advisor had no independent effect, $F < 1$, nor did analyses show interactions between the participants' gender or the advisors' (ostensible) gender and the facial characteristics of the advisor, all F's < 1.

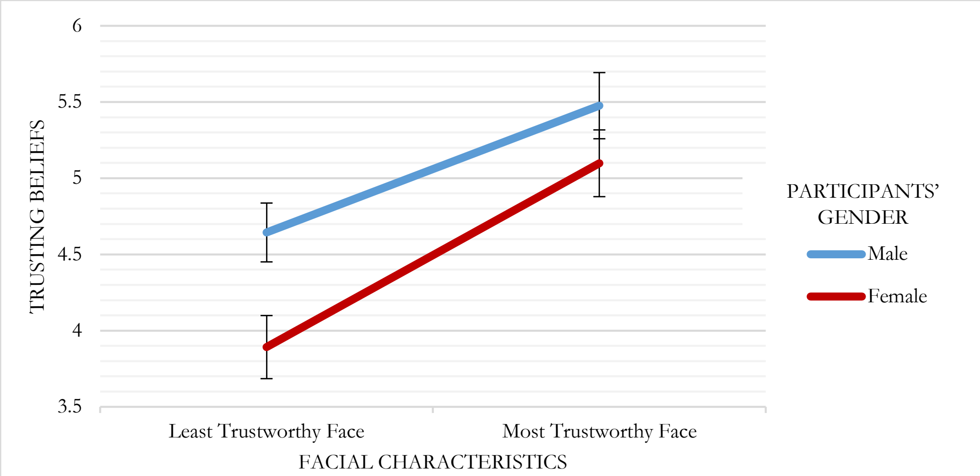

Figure 6.7: Mean and standard error of trusting beliefs scores by advisor's facial characteristics (least trustworthy face vs. most trustworthy face) and participants' gender (male vs. female). Male participants reported higher trusting beliefs about an advisor (independent of the advisor's facial characteristics) compared to female participants. Participants (independent of their gender) reported higher trusting beliefs about the most trustworthy face advisor (vs. the least trustworthy face advisor). Results showed no interaction effect between participants' gender and the advisor's facial characteristics on trusting beliefs.

As Figure 6.7 depicts, female participants held the lowest trusting beliefs towards the advisor with the least trustworthy face (M = 3.89, SD = 1.23), while male participants rated the advisor with the most trustworthy face as the most trustworthy advisor (M = 5.48, SD = 0.87).

Several conclusions stem from these analyses. First, that trusting beliefs towards the least trustworthy face were always lower than towards the most trustworthy face independent of the participants' gender (in line with *H2(a)*). Second, male participants were more successfully persuaded to believe that the advisor was trustworthy than female participants (adjacent to the outcome in *H2(b)*). Overall, female participants held the lowest trusting beliefs towards the advisor with the least trustworthy face while male participants rated the advisor with the most trustworthy face as the most trustworthy advisor.

In summary, these analyses demonstrated clearly that robots with facial characteristics that humans consider trustworthy enhance trusting beliefs towards the robot, independent of its gender. Moreover, this effect seemed to be stronger for male participants rather than female participants.

Hypothesis 4: Correlation between Psychological Reactance, Compliance and Trusting Beliefs

A Pearson product-moment correlation coefficient was computed to assess the relationship between psychological reactance, compliance and trusting beliefs (dependent variables) that were used in the previous hypotheses. No significant correlation was found between psychological reactance and compliance, r = -0.02, p = 0.85 *(n.s.)*. A strong negative correlation (2-tailed) was found between psychological reactance and trusting beliefs, $r = -0.74$, $p < 0.001$. Thus a drop in psychological reactance was correlated with higher trusting beliefs, but not with compliance.

6.3.3 Exploratory Analysis

Inherent Confounds on Facial Characteristics of the Robot

To assess the manipulation involving the facial characteristics of the advisor, a MANOVA test was performed using attractiveness and healthiness scores as dependent variables, the least and the most trustworthy faces of the advisor as the independent variable. The demonstrator with the neutral face was used as a baseline for these measurements (attractiveness and healthiness of neutral facial characteristics are equal to zero) and the difference of scores of attractiveness and healthiness between the demonstrator and the advisor were examined. The results showed a significant main effect of facial characteristics on the robot's attractiveness and healthiness scores with *Wilks' Λ* = 0.71, $F(2, 69) = 14.16$, $p < 0.001$. Figure 6.8 shows the scatter plot of the advisor's facial characteristics vs. attractiveness and healthiness scores of the agent.

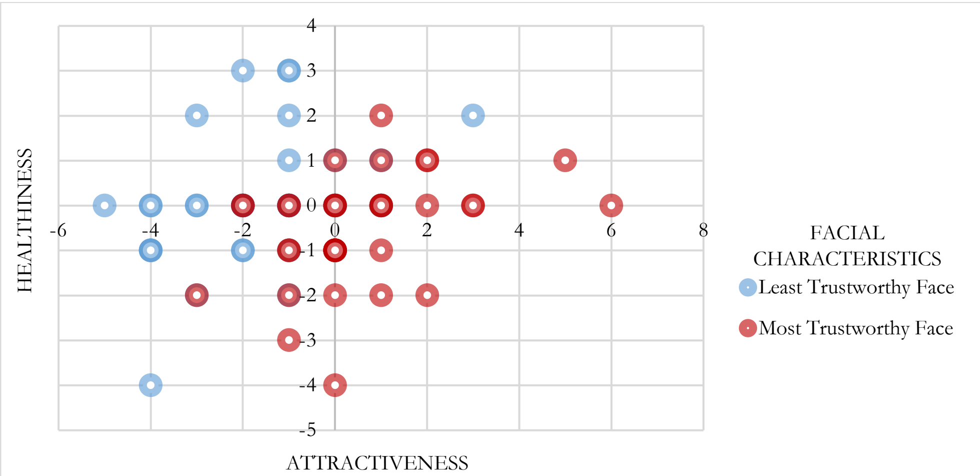

Figure 6.8: Mean attractiveness and healthiness of the advisor scores by advisor's facial characteristics (least trustworthy face vs. most trustworthy face) with neutral facial characteristics as 0. Participants reported higher attractiveness and healthiness scores about the most trustworthy face advisor (vs. least trustworthy face advisor).

For the attractiveness factor, an advisor with the most trustworthy face scored slightly higher than neutral attractiveness $M = 0.53$ ($SD = 1.72$) while an advisor with the least trustworthy face fall in the unattractive range, $M = -1.69$, $SD = 1.72$. An ANOVA test confirmed a significant main effect of facial characteristics of the advisor on the attractiveness, $F(1, 70) = 28.46$, $p < 0.001$, partial $\eta^2 = 0.29$. Moreover, the results showed marginal a significant main effect of the healthiness measure with facial characteristics, $F(1, 70) = 3.74$, $p = 0.057$, partial $\eta^2 = 0.05$. Also, the results revealed that the participants perceived the advisor with the least trustworthy face was less healthy ($M = -0.53$, $SD = 1.52$) compared to the advisor with the most trustworthy face ($M = 0.08$, $SD = 1.13$).

Chapter 6

Mediation Analysis

To test suspected mediation between the dependent and independent variables, three mediation analyses (one for each dependent variable stated in the hypothesis: psychological reactance, compliance and trusting beliefs) were conducted following the steps of mediation analysis developed by (Baron & Kenny, 1986). Model testing hypotheses for mediation analysis 1, mediation analysis 2 and mediation analysis 3 can be seen in Figure 6.9. Details for each mediation analysis was described in the following subsections.

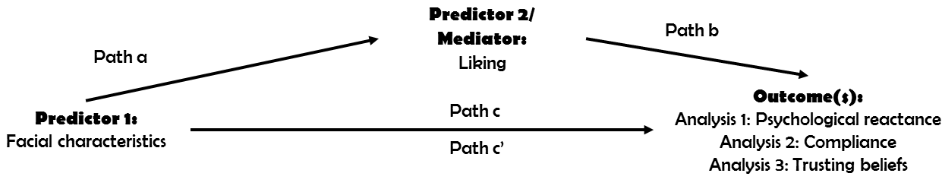

Figure 6.9: Liking rate fully mediates the relationship between facial characteristics and both psychological reactance (in analysis 1) and trusting beliefs (in analysis 3). However, liking rate did not mediate the relationship between facial characteristics and compliance (in analysis 2).

<u>Analysis 1: Psychological Reactance</u>

Regression analysis was used to investigate whether liking mediates the effect of facial characteristics (causal variable) on psychological reactance. Because (as described above) results showed that facial characteristics influenced (as the main effect) the repeated measure (combining measure negative cognitions and feelings of anger) of psychological reactance, we calculated a psychological reactance score for each participant by averaging the participant's score on feelings of anger and on negative cognitions. First, this analysis showed that facial characteristics were a significant predictor of psychological reactance (B = -0.50, SD = 1.44), t = -4.86, $F(1, 70)$ = 23.64 (path c). Next, results confirmed that facial characteristics was also a significant predictor of liking (B = 0.56, SD = 1.95), t = 5.71, $F(1, 70)$ = 32.62 (path a). Again, we checked whether the mediator (liking) affected the outcome (psychological reactance). Indeed, liking was a significant predictor of psychological reactance (B = -0.81, SD = 0.42), t = -11.46, $F(1, 70)$ = 131.37 (path b). Finally (step 4), this analysis showed that the effect of facial characteristics on psychological reactance became non-significant when taking into account liking as a mediator (B = -0.07, SD = 1.19), t = -0.81, $F(2, 69)$ = 65.69 (path c').

These results support the hypothesis that liking is a full mediator of the relationship between the facial characteristic and psychological reactance.

<u>Analysis 2: Compliance</u>

To investigate whether liking mediates the effect of facial characteristics on compliance, we conducted a second linear regression analysis. First, this analysis showed that facial characteristics were a significant predictor of compliance (B = 0.24, SD = 4.41), t = 2.03, $F(1, 70)$ = 4.12 (path c). Next, results confirmed that facial characteristics was a significant predictor of liking (B = 0.56, SD = 1.95), t = 5.71, $F(1, 70)$ = 32.63 (path a). Again, we checked whether the mediator (liking) affected the outcome (compliance). Indeed, liking was not a significant predictor of compliance (B = 0.11, SD = 1.95), t = 0.91, $F(1, 70)$ = 0.83 (path b). As the relationship in path b was not significant, it can be concluded that mediation was not possible.

Thereby, we reject the hypothesis that liking is a mediator of the relationship between facial characteristics and compliance.

Analysis 3: Trusting beliefs

The third linear regression analysis was conducted to investigate whether liking mediates the effect of facial characteristics on trusting beliefs. First, this analysis showed that facial characteristics were a significant predictor of trusting beliefs (B = 0.43, SD = 1.95), t = 3.96, F(1, 70) = 15.68 (path c). Second, we checked for a positive relationship between facial characteristics and liking. Results confirmed that facial characteristic was a significant predictor of liking (B = 0.56, SD = 1.95), t = 5.71, F(1, 70) = 32.63 (path a). Third, we checked whether the mediator (liking) affected the outcome (trusting beliefs). Indeed, liking was a significant predictor of trusting beliefs score (B = 0.89, SD = 0.42), t = 15.97, F(1, 70) = 255.02 (path b). Finally, this analysis showed that the effect of facial characteristics on trusting beliefs became non-significant when taking into account liking a mediator (B = -0.11, SD = 1.19), t = -1.58, F(2, 69) = 131.49 (path c').

These results support the hypothesis that liking is a full mediator of the relationship between facial characteristic and trusting beliefs.

Anthropomorphism and Perceived Intelligence

A two-way ANOVA was conducted to determine if the anthropomorphism score of the social agent (in this case the advisor) was biased by the manipulations of facial characteristics portrayed by the advisor and gender similarity of the advisor and participants. There was no significant relationship found between all three measured factors, namely, facial characteristics and gender similarity (independent variables) toward anthropomorphism (dependent variable), F(1, 68) = 1.26, p = 0.27 *(n.s)*. Thus, the independent variables used in this chapter did not increase the anthropomorphism value of the agent used (as an advisor) during the interaction.

Furthermore, an ANOVA test showed that there was no significant effect of facial characteristics and gender similarity of the advisor and participants upon perceived intelligence, F(1, 68) = 1.55, p = 0.22 *(n.s.)* but there was a significant relationship between facial characteristics on the perceived intelligence with F(1, 68) = 5.48, p = 0.02, partial η^2 = 0.07. Additional analysis on the influence of facial characteristics towards perceived intelligence revealed that the most trustworthy face (M = 3.84, SD = 0.60) was perceived as more intelligent compared to the least trustworthy face (M = 3.49, SD = 0.69).

6.4 Discussion

In this study, participants were asked to play a trust game with SociBot, where the SociBot attempted to persuade them regarding ten different choices for making a beverage for an alien. The advisor's facial characteristics (least trustworthy face vs. most trustworthy face) and gender similarity (similar vs. opposite) were manipulated in a between-subjects experiment. Participants' psychological reactance, compliance and trusting beliefs responses were measured. In line with the Media Equation hypothesis (Reeves & Nass, 1996), we expected that basic social characteristics presented by social actors suffice to elicit social responses. So, we anticipated that participants in our experiment would also show some social responses (psychological reactance, compliance and trusting beliefs) toward the SociBot.

Providing evidence for H1(a), results showed that facial characteristics of the advisor influenced the participant's psychological reactance. Participants felt higher reactance towards a robot with the least trustworthy facial characteristics compared to the one with the most trustworthy characteristics. This finding may have been because participants were more attracted to the most trustworthy advisor (see Figure 6.8). As highlighted by earlier research (Oosterhof & Todorov, 2009; Sacco & Hugenberg, 2009; Todorov et al., 2015), the facial characteristics of the advisor used in this study related to emotional expressions. That is, the least trustworthy characteristics are associated with angry-looking faces while the most trustworthy characteristics of faces showing a positive emotion/mood (i.e., happy). Therefore, it could be that participants felt more reactant by having intense interactions with the robot featuring the least trustworthy facial characteristics.

Additionally, H1(b) showed an influence of gender similarity on psychological reactance (especially negative cognitions). That is, participants experienced lower psychological reactance when interacting with a similar gender advisor than with an opposite gender advisor. These results are in line with the similarity-attraction hypothesis (Byrne, 1971) and with earlier studies which demonstrated similarity preference in human-robot interaction (Eyssel et al., 2012), especially for young children (Sandygulova & O'Hare, 2018) and in human-human interaction (Lalonde, Bartley, & Nourbakhsh, 2006), especially for female participants (Lockwood, 2006). Surprisingly, female advisors caused higher psychological reactance than male advisors. In our study, both male and female advisors actually delivered the same advisory dialogues and used similar facial expressions in conveying exactly the same advice. Still, participants felt angrier and had more negative cognitions towards the female advisor than towards the male advisor.

A significant relationship was found between facial characteristics of the robot on compliance in H2(a). As the participants perceived the most trustworthy faced advisor as more intelligent than the least trustworthy face advisor (from the score of perceived intelligence as shown in exploratory analysis), the participants who interacted with the advisor with the most trustworthy face were willing to take the risk of losing one extra credit by letting the advisor make the selections on behalf of them and complied to the selection. In contrast, participants in the least trustworthy face condition preferred to save their credit by making their own prediction and to guess the right answer rather than comply with the advisor. Some earlier studies (Ballew & Todorov, 2007; Todorov, Mandisodza, Goren, & Hall, 2005) have shown that judgments of competence from faces could affect compliance. However, this earlier research did not model precisely which types of facial characteristics might invoke competency.

Our results did not find the expected influence of gender similarity on compliance as expected in H2(b). Female participants demonstrated higher compliance towards the advisor independent of its gender by asking the robot to make the selections on their behalf more often than men did. This finding is in agreement with an earlier study (Buchan, Croson, & Solnick, 2008) wherein an investment game with a similar decision structure male participants viewed the interaction more strategically than female participants by not investing their money or credits to ask for helps in the human-human interaction. Also, in line with the findings of Buchan et al. (2008) in human-human interaction, both male and females participants showed higher compliance when their interaction partner (in this study, the advisor) was female (compared to a male advisor).

As expected in H3(a), the advisor's facial characteristics have a significant effect on the trusting beliefs towards the advisor. That is, participants reported higher trusting beliefs towards the advisor with the most trustworthy facial characteristics than towards the one with the least trustworthiness face. Independent of the advisor's gender, male participants (compared to female participants) believed that the robotic advisor could be trusted more. Thus, it can be suggested that facial characteristics are essential for persuading the participants (especially male participants) to evaluate the robotic advisor to be trustworthy. This result is in line with neuropsychological research (Todorov et al., 2008), which suggested that the response to trustworthy faces is hard-coded in our brains; there is a part of the human brain (the amygdala) that responds to trust-related facial characteristics of faces presented on-screen. Although our study did not investigate brain area activation, we showed that facial characteristics of the robot activated trustworthiness judgments, just as was found in these earlier studies (Jeanquart-Barone & Sekaran, 1994; Todorov & Oosterhof, 2011). Furthermore, the current research extends earlier findings in social psychology (Jeanquart-Barone & Sekaran, 1994; Todorov & Oosterhof, 2011) by showing that facial characteristics of a distinctly non-human, robotic social entity can activate trustworthiness judgments and compliance. Earlier research (Todorov et al., 2008; Todorov et al., 2015) showed that facial characteristics of artificial faces on the screen could influence trustworthiness judgments of human perceivers. Importantly, the current results are the first to show these effects in the context of human-robot interaction.

Our results did not find the expected influence of gender similarity on trusting beliefs as anticipated in H3(b). That is, participants did not report significantly more trusting beliefs for the robot having the same gender as them. This finding did not confirm earlier studies that suggested that gender similarity (Byrne, 1971) between the participants (users) and the advisor (robotic partner) influenced trusting beliefs (Eyssel & Hegel, 2012; Goetz et al., 2003). A potential explanation might be that the advisor's task is not associated with any explicit gender stereotypes, so participants held no expectations as to whether a male or female advisor should know the alien's taste better. Earlier research has indeed shown that gender stereotyping of tasks was manifested in the interaction among real humans (Eagly, 1997; Jeanquart-Barone & Sekaran, 1994) and also in the interaction between a human and a robotic partner (Kuchenbrandt et al., 2014; Tay et al., 2014).

More importantly, mediation analysis showed that liking was a full mediator for psychological reactance (feelings of anger and negative cognitions). That is, psychological reactance was only triggered if the participants did not like the advisor. Mediation analysis also revealed that trusting beliefs were entirely driven by the liking rate towards the robot. The more the participants liked the robot, the more participants believed it could be trusted. In other words, the facial characteristics of the robot featuring the least trustworthy face caused participants to have less trusting beliefs due to the fact that the participants did not like the least trustworthy facial characteristics. In contrast, results provided no evidence that liking mediated the relationship between the robot's facial characteristics and the participant's compliance towards the selection made by the robot. So, irrespective of whether the participants expressed like or dislike towards the robot, they asked for its help if they found it risky to make the selections themselves. In general, the decision to ask for help from the robot was affected only by the facial characteristics of the robot. The more trustworthy the robot's face, the more often participants requested its help. To sum up, liking the robotic advisor triggered less psychological reactance and caused higher trusting beliefs, but did not affect compliance. Thus, our mediation analyses explain the negative correlation found in H4 between trusting beliefs and psychological reactance. It seems that if people like a robotic advisor, they believe it can be trusted resulting in lower psychological reactance, but this is not reflected in their compliance.

6.5 Summary

This chapter has made the following contributions; (1) we have shown how appropriate design of the facial characteristics of a robot can invoke low psychological reactance, engender high trusting beliefs and high compliance in human-robot interaction, and (2) we have illustrated how similarity in gender between users and the persuasive robot induces lower psychological reactance (lower negative cognitions about the robot) than interaction with a robot of the opposite gender, and (3) through mediation analyses we have found that liking of the robot (depending on its facial characteristics) is a full mediator for psychological reactance and trusting beliefs. Finally, (4) we have found that lower psychological reactance was correlated with higher trusting beliefs, but not with compliance. From a practical standpoint, our results demonstrated that persuasion could be more effective and cause less reactance by designing facial characteristics of robots to match those known from interpersonal psychology to evoke trusting beliefs in people, and by personalizing persuasive robots to match the gender of the user. Moreover, since liking has been shown to have a mediating role, it appears that a very generic mechanism for enhancing persuasiveness and reducing psychological reactance is to design robots that will be more likeable, which could potentially be achieved by simpler means such as the static external appearance of the robot.

Despite positive effects of non-interactive social cues (especially facial characteristics of the robots) on human social responses, we argue that interactive social cues could be advantageous especially for social robots in persuading people. Also, we are interested to investigate the role of liking (which was found to be a mediating factor in this chapter) in the design of persuasive robots so that people will believe the robot can be trusted and will not make them feel psychological reactance.

Therefore in the next chapter, we investigate the effect of interactive social cues: head mimicry and proper timing for social praises on social responses (psychological reactance, compliance, trusting beliefs and liking). We assume that interactive social cues can foster positive social responses on persuasive attempts.

CHAPTER 7

Investigating Interactive Social Cues: Head Mimicry and Social Praise Boost Trusting Beliefs, Knock Down Reactance

This chapter is based on a published paper:

Assessing the Effect of Persuasive Robots Interactive Social Cues on Users' Psychological Reactance, Liking, Trusting Beliefs and Compliance (2019). *Advanced Robotics,* 1-13. DOI: 10.1080/01691864.2019.1589570

In Chapter 6, we have reported that facial characteristics that people tend to trust more in humans and similar gender between robot and users decrease psychological reactance in persuasive attempts. It is however not clear how users respond socially to persuasive social robots and whether such reactions will be more pronounced when the robots feature more interactive social cues. In this chapter, we examine social responses towards persuasive attempts provided by a robot featuring different numbers of interactive social cues. A laboratory experiment assessed participants' psychological reactance, compliance, trusting beliefs and liking toward a persuasive robot that either presented users with: no interactive social cues (random head movements and random social praises), low number of interactive social cues (head mimicry), or high number of interactive social cues (head mimicry and proper timing for social praise). Results showed that a persuasive robot with the highest number of interactive social cues invoked lower reactance and was liked more than the robots in the other two conditions. Furthermore, results suggested that trusting beliefs towards persuasive robots can be enhanced when the robot providing praise independent of the timing. However, interactive social cues did not contribute to higher compliance.

7.1 Introduction

A few studies have investigated how people respond to persuasive attempts by social robots e.g., Roubroeks et al. (2009) and Verberne, Ham, Ponnada, and Midden (2013). Nevertheless, the aforementioned investigations implemented what can be characterized as *static* or *non-interactive* social cues into persuasive social robots rather than *interactive* ones. Non-interactive social cues refer to the cues that are fixed and changeless while interactive social cues refer to the cues that can be changed according to the situation at hand or the needs of the person they interact with (Hehman, Flake, & Freeman, 2015). We argued that it is crucial to study whether a persuasive social robot displaying more *interactive* social cues causes more or less social responses because most social cues in real life interactions between people are interactive, and robots will be more lifelike if interactive social cues are implemented onto the robots instead of non-interactive ones. Earlier research has highlighted the importance of socially interactive robots in changing human behaviour and attitudes research (de Ruyter, Saini, Markopoulos, & Van Breemen, 2005; Fong, Nourbakhsh, & Dautenhahn, 2003; Markopoulos, de Ruyter, Privender, & van Breemen, 2005). Robots with non-interactive social cues execute pre-programmed behaviours and dialogues, regardless of the reactions by humans. Examples of such social cues are gender, facial expressions and pre-programmed behaviours like head movement of a robot. On the other hand, interactive social cues are exhibited only when the robot social cues are in response to the users' behaviour or give some context or situation-specific responses (Kaptein et al., 2011).

A clear illustration of interactive social cues in human-human interaction is when Person A turns his head (the first example of interactive social cues) with a puzzled expression (the second example of interactive social cues) when suddenly Person B pats him on the shoulder from behind. Without a touch from Person B such a behaviour by Person A might not be triggered at all. Breazeal (Breazeal, 2003) suggested that what she called 'sociable robots' are pro-actively engaged with people to fulfil internal social aims such as sharing mutual emotions between humans and robots. Earlier research in human-robot interaction (Kaptein et al., 2011; Robins &

Dautenhahn, 2014; Verberne, Ham, & Midden, 2015) demonstrated that people manifested positive responses (higher trusting beliefs, initiating joint attention, making eye contact and perceived friendliness) towards robots that exhibit interactive cues such as mimicry, interactive facial expressions and social praise. Thus, we argue that persuasive robots should use interactive social cues such as mimicry and social praises in maintaining positive social relationships with the human persuadee and thus enhance their effectiveness along with how the persuadee experiences the interaction with the robot.

A related study on mimicry (Stel, Rispens, Leliveld, & Lokhorst, 2011) claimed that social responses towards robots ignited if both parties (the mimicker and the mimickee) share the same emotional and cognitive states. Empirical studies have shown that when a mimicker (either robot or human) imitated the movements (Chartrand & Bargh, 1999; Verberne, 2015), accent (Adank, Stewart, Connell, & Wood, 2013), reciprocal (Zhou, 2012) and facial expressions (Stevens et al., 2016) of the mimickee, the positive responses for instance liking and trusting beliefs towards the mimicker increase. In this way, mimicry has been shown to be one of the most powerful interactive social cues which can lead to positive impressions for such interaction. In line with similarity-attraction theory (Byrne, 1971), earlier research in an automotive setting (Verberne, Ham, Ponnada, & Midden, 2013) has shown that mimicry of head movements by avatars can increase social responses in humans, such as trusting beliefs and liking towards the agents. However, we argued that this finding (Verberne et al., 2013) was rather weak due to the mimicry of a 2D interaction by an on-screen partner and the non-realistic interaction social robots could offer.

Mimicry is one of several interactive social cues by robots that have been assessed formerly in human-robot interaction. Another example pertains to interactive social cues is social praise. Experimental studies from neuroscientists showed that social praise triggers the release of the neurotransmitter which is known as dopamine, that is associated with pleasure (Esch & Stefano, 2004). As suggested by the Media Equation hypothesis (Reeves & Nass, 1996), several experimental studies attempted to identify how humans perceived social praise by machines like robots. For example, a study by Kaptein et al. (2011) showed that humans positively perceived social praise by an iCat robot. Humans' motivation for learning, exercising for pleasure and rehabilitation (Fasola & Matarić, 2013; Malik, Yussof, & Hanapiah, 2017; Tanizaki et al., 2017) could be increased through the use of praise or encouragement by robots as well. Importantly, earlier study showed that timing in which the social praise was delivered has a significant bearing on its effectiveness (Kaptein et al., 2011). However, no earlier study has yet examined the effect of interactive social praise especially on psychological reactance by persuasive robots.

This current chapter extends the state of the art as described above, by investigating how interactive social cues impact interaction with persuasive robots. Specifically, this chapter reported an experiment that examined the influence of the number of interactive social cues that the robot displays upon users' psychological reactance, compliance, trusting beliefs and liking towards the robotic persuader. The interactive social cues under investigation include head mimicry (off: a robot with random head's movement vs on: a robot with head mimicry) and social praise (random timing vs none vs proper timing). Based on Social Agency theory (Mayer et al., 2003), it can be anticipated that responses towards social communicators with stronger social cues (in our case the persuasive robots with interactive social cues) will be analogous to the responses towards the human-human interaction. Thus, we expected that robots with interactive social cues: head mimicry (Verberne, 2015) and social praise with proper timing (Kaptein et al., 2011) will evoke positive social responses including high liking and trusting beliefs towards the robot. However, we could not predict how interactive social cues of robots will affect psychological reactance and compliance as earlier research has not yet examined them.

The Current Study

In this study, we investigated the influence of interactive social cues on persuasion activity upon psychological reactance, compliance, trusting beliefs and liking. Besides, this study also examined how psychological reactance experienced from the persuasive attempts influences compliance, trusting beliefs and liking towards the persuasive robot. We used a higher level of social agency (a physical robot) as a mimicker compared to virtual agents used in earlier research (Verberne et al., 2013). In the current study, we used the SociBot (which was also used in the studies reported earlier in this thesis) as a persuader implementing the interactive social cues: head mimicry and social praise with proper timing (for brevity, we refer to proper timing for social praises simply as interactive social praise in the remainder of this thesis).

Participants were asked to interact with the robot that was programmed to have three conditions: no interactive social cues vs. low number of interactive social cues vs. high number of interactive social cues to answer the question whether a robot that has more interactive social cues will be perceived more positively than the robot with less interactive social cues. We implemented a robot that mimics participants' head movements (the first interactive social cue) and interactively praises the participants (the second interactive social cue). Specifically, the hypotheses for the current study were:

- H1. There is a significant difference in psychological reactance score between participants interacting with a persuasive robot featuring higher number of interactive social cues and those interacting with a persuasive robot with lower number of interactive social cues
- H2. There is a significant difference in compliance score between participants interacting with a persuasive robot with higher number of interactive social cues and those interacting with a persuasive robot with lower number of interactive social cues
- H3 There is a significant difference in trusting beliefs score between participants interacting with a persuasive robot with higher number of interactive social cues and those interacting with a persuasive robot with lower number of interactive social cues
- H4 There is a significant difference in liking score between participants interacting with a persuasive robot with higher number of interactive social cues and those interacting with a persuasive robot with lower number of interactive social cues
- H5 Psychological reactance has a significant correlation to compliance, trusting beliefs and liking

7.2 Materials and Methods

7.2.1 Participants and Design

We recruited twenty-one participants (9 male and 12 female) aged between 26 and 41 (M = 30.9, SD = 4.00). A 1x3 (number of interactive social cues: a robot with no interactive social cue vs low number of interactive social cues vs high number of interactive social cues) within-subjects experimental design was used. Experimental sessions lasted 45 minutes per participant for which participants were given a €7.5 voucher as a token of appreciation. All participants were employees of the Eindhoven University of Technology.

To limit the "carryover effects" of the within-subject experimental design (Myers, Well, & Lorch Jr, 2013), the order of the three interactive social cues conditions was randomised for each participant. For instance, some participants interacted with the robot showing no interactive social cue in their first session, followed by the robot showing a high number of interactive social cues in their second session, and a robot showing low number of interactive social cues in their last session. For enhancing the study design and reducing carryover effects from the previous session, the robot's face and voice, type of exercises in the first activity, the theme of the pictures used in the second activity, the persuasive dialogues for both the first and the second persuasion attempts were also randomised.

7.2.2 Manipulations of Interactive Social Cues

As mentioned earlier, we manipulated the number of interactive social cues implemented on the persuasive robot. In all three conditions, the SociBot was positioned on a desk in front of the participants and preprogrammed with verbal and nonverbal social cues (see Figure 7.1).

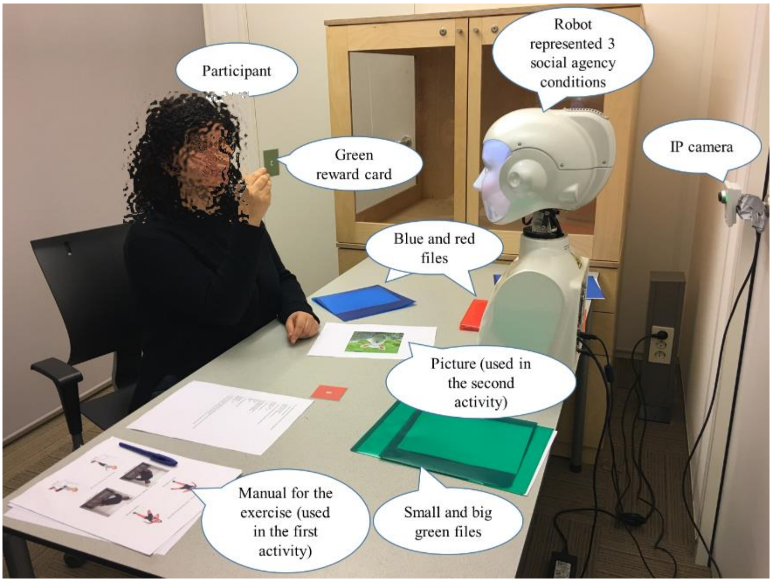

Figure 7.1: Experimental set ups.

In the no interactive social cue condition, the robot interacted with the participant using random head movements (independent of the participant's head movement) and social praise delivered at random moments (independent of the participant's actions). In the low number of interactive social cues condition, the robot interacted with the participant while mimicking the participant's head movement. In the high number of interactive social cues condition, the robot mimicked the participant's head movement and also praised the participant at appropriate moments in the interaction. The robot praised the participant at random moments in time (e.g., which could also mean suddenly saying *'Good job'* before the participant had made any decision) in the no interactive social cue condition, but at appropriate moments in the interaction in the high number of interactive social cues condition (e.g., praised the participant by saying "*Good job*" only after the participant complied to the robot's advice). No social praise was given to participants in the low number of interactive social cues condition.

In all conditions, the robot was operated by the experimenter using a Wizard of Oz prototyping technique for choosing pre-selected dialogues at suitable moments during the interactions, including the social praise conveyed by the robot in the high number of interactive social cues condition. Additionally, the robot's head was preprogramed to automatically mimic participants' head movements in X and Y axes for high and low number of interactive social cues conditions using integrated IR depth sensor embedded within the torso of the robot. Random head movements were presented during the interaction with the robot in no interactive social cue condition.

7.2.3 Task

The participants were asked to interact with a robot three times. In each of these three sessions, the SociBot displayed interactive social cues differently (fitting the manipulation of interactive social cues as described above). Each session was divided into two activities. In the first activity, participants were asked to do a simple three-minute exercise instructed by the robot. Participants were given a short, printed guideline leaflet describing the type of exercises and guidance on how to do these exercises step-by-step. Exercises for the first activity including standing on one leg, weight shifting, and sit-down, stand-up exercises. This activity was designed to increase the awareness of head mimicry by the robot (if any). As such, there were no persuasive attempts involved in the first activity.

The robot started the persuasive attempts in the second activity, in which the participants were asked to make choices in two tasks. The first task was a picture card selection task, where participants were asked to select which one of the two picture they liked, and then to describe that picture to the robot in one minute. The second was a reward card selection task, where participants were asked to select one of three alphabet cards (card A, B or C) they liked as their reward. To ensure the fairness of the reward offered, the participants were given the same reward (the €7.5 voucher as mentioned earlier) at the end of the experiment, independent of the alphabetical reward card chosen. These two selection tasks each involved a persuasive attempt by the robot, in which the robot would persuade the participants to change their initial selection to another card (change picture in the first attempt and change the reward card in the second attempt). The robot never agreed with any initial selections made by the participants, and it always tried to push the participants to change their selections.

Before these selection tasks, it had been emphasised by the experimenter that the participants could freely choose between two responses, i.e., keep their initial selections (ignore the advice), or change their mind and make other choices (follow the advice). Participants were also reminded several times that there were no absolute right or wrong answers in this game. During the persuasive attempts, the robot used forceful, highly coercive language to increase the likelihood of compliance in accordance to our findings in Chapter 3.

7.2.4 Procedure

The experiment was conducted at the Department of Industrial Design, Eindhoven University of Technology. Participants were greeted by the experimenter upon arrival to a designated room, and asked to take a seat against a table facing the robot that was placed on the table. Six plastic folders in three different colours (red, green and blue - one colour for each session; and one small and one big folder for each colour) were placed on the table. Each coloured folder (big and small folders) represented different sessions. The three small folders contained two printed pictures of a theme (animals, vacation destinations and portraits) that would be used in the picture card selection task. Meanwhile, the three big folders contained alphabetical coloured reward cards with three alphabetical-options (A, B and C) to be used in the reward card selection task and a set of questionnaires to be answered by the participants after the persuasive attempts at the end of each session. An Internet Protocol (IP) camera was placed near to the robot to record the activities during the experimental session (see Figure 7.1).

Before filling in the demographic information, the participants were asked to read and sign a consent form containing the procedure of the experiment and agreement for video recording. In the consent form, participants were notified that their participation was entirely voluntary, and that they had the right to withdraw their permission to use the data recorded by notifying the experimenter up to 24 hours after the session. They could also refuse to participate in the experiment without having to provide any reasons and stop their participation at any time during the experimental session. The experimenter would leave the room after ensuring the participants were fit to undergo the exercise by asking the participants themselves and had no further questions.

The robot started the first session by greeting the participant so that (s)he was aware of the role and the identity (face and voice) of the robot. After that, the robot briefly explained all the activities that needed to be done by the participants in that specific session. The first activity involved exercise. After completing the first activity, the persuasive attempts took place as the robot started the second activity. Participants were required to participate in two task selections: picture card selection and reward card selection. After completing the second activity, the participants were asked to fill in the questionnaire consisting of psychological reactance, trusting beliefs and liking items in evaluating the designated social agent. The following session would start after the participants would tell the robot '*I am done*' upon which the social agent would change its identity (face and voice).

The whole procedure was repeated in three consecutive sessions each featuring different number of interactive social cues of a robot. The experimenter debriefed the participants and presented a voucher as a token of appreciation at the end of the experiment.

7.2.5 Measures

As there were three sessions of the experiment (led by the robot with different number of interactive social cues), participants were asked to complete the questionnaires described below three times.

Psychological Reactance

Based on the Intertwined Model of Reactance (Dillard & Shen, 2005; Rains & Turner, 2007), we took two measures of psychological reactance based on self-report: feelings of anger and negative cognitions as in earlier chapters (see also Shaver et al. (1987)).

Compliance

As in earlier chapters, we assessed the compliance to the robot as follows: If the initial and the final selections were inconsistent, the participants would be awarded 1-point for each selection. For example, if a particular participant changed his/her choice of a picture and reward-card as asked by the robot, then the participant would be given the compliance score of 2. However, if the participant changed only the initial picture or only the initial reward card then they would be given a score of 1. If participants would ignore the advice and keep to their initial selections, they would be given a score of 0.

Trusting beliefs

To assess how high the associated number of interactive social cues on trusting beliefs, we used the questionnaires developed by Heerink et al. (2009) and Tay et al. (2014). To keep the simplicity of our questionnaire, only three statements were used to estimate the trusting beliefs and: *"I will trust Robin* (e.g. name of the social agent) *if he gives me advice again in the future", "I trust that Robin can provide me with good suggestions",* and *"I will follow the advice that Robin gives me"* in 5 point-Likert scales with level ranging from completely disagree (1) to completely agree (5). The trusting beliefs measurement was found to be highly reliable (Cronbach's α = 0.85).

Liking

The liking rate of the robot was rated using 9-point semantic differentials from the Godspeed Questionaire (Bartneck, Kulić, Croft, & Zoghbi, 2009) indicating that "*Please rate your impression of David* (e.g. name of the social agent) *on these scales*": *dislike/ like, unfriendly/ friendly, unkind/ kind, unpleasant/ pleasant* and *awful/ nice.* This liking rate was assessed after the persuasive attempts by the agents at the end of each session. Cronbach's α for the five liking items of a persuasive robot was 0.81.

7.3 Findings: Hypothesis Testing

Hypothesis 1: Psychological Reactance

In analysing the effect of the number of interactive social cues on psychological reactance, we run a repeated measure Analysis of Covariance (ANCOVA) test by comparing the scores of 3 (number of interactive social cues: no vs low vs high) x 2 (elements of psychological reactance: feelings of anger and negative cognitions). This analysis indicated a significant main effect of the number of interactive social cues, $F(2, 18) = 7.62$, $p = 0.004$, partial $\eta^2 = 0.46$ for which

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hypothesis 1 was accepted. Mauchly's Test of Sphericity indicated that the assumption of sphericity had not been violated in this test, $\chi^2(2) = 0.81$, $p = 0.14$. The linear test of within-subjects contrasts also demonstrated a significant relation between the independent and dependent variables, $F(1, 19) = 14.70$, $p = 0.001$, partial $\eta^2 = 0.44$. In line with our hypothesis, this main effect showed that participants reported the highest reactance towards the persuasive robot in no interactive social cues condition ($M = 1.98$, $SD = 0.84$), followed by the robot in low number of interactive social cues condition ($M = 1.75$, $SD = 0.94$) and the lowest reactance when interacting with the robot in high number of interactive social cues condition ($M = 1.57$, $SD = 0.62$).

We performed two separate repeated measure ANCOVAs to examine the individual components of psychological reactance scores (the first ANCOVA for the feelings of anger and the second ANCOVA for the negative cognitions) resulting from the manipulations of the number of interactive social cues (see Figure 7.2).

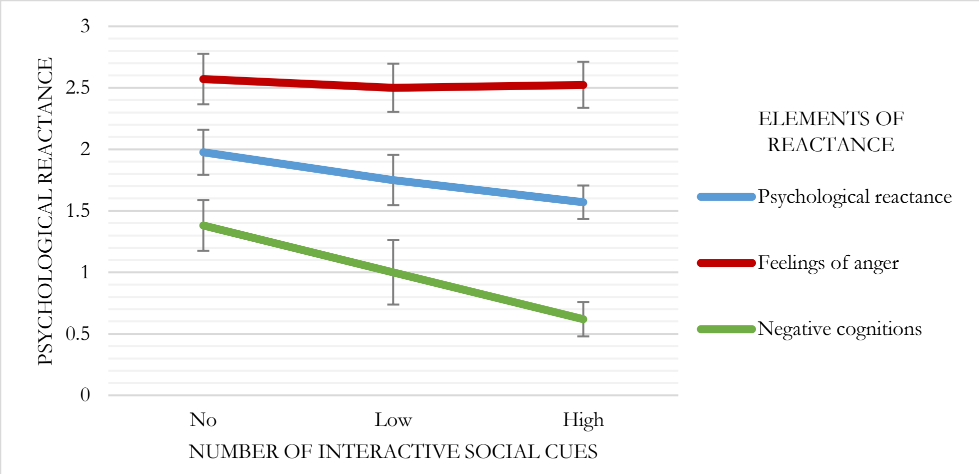

Figure 7.2: Mean and standard error of psychological reactance (with individual components of reactance: feelings of anger and negative cognitions) on persuasive robot scores by the number of interactive social cues. Participants reported the highest reactance on the robot in no interactive social cue condition, and the lowest reactance for the robot in high number of interactive social cues condition. The lowest feelings of anger scores were recorded by the robot in low number of interactive social cues condition.

Several main results related to the individual components of psychological reactance measured were found. First, there was a significant main effect of the number of interactive social cues on feelings of anger, $F(2, 18) = 10.44$, $p = 0.001$, partial $\eta^2 = 0.54$. Mauchly's Test of Sphericity indicated that the assumption of sphericity had not been violated in this test, $\chi^2(2) = 0.92$, $p = 0.63$. The linear test of within-subjects contrasts also demonstrated a significant relation between the independent, dependent and covariate variables, $F(1, 19) = 22.93$, $p < 0.001$, partial $\eta^2 = 0.55$. Results showed participants experienced the highest feelings of anger interacted with the robot in no interactive social cue condition ($M = 2.57$, $SD = 0.94$), followed by the robot in high number of interactive social cues condition ($M = 2.52$, $SD = 0.86$) and the lowest feeling of anger was recorded in low number of interactive social cues condition ($M = 2.50$, $SD = 0.90$).

Second, the number of interactive social cues manipulation resulted in a significant main effect for negative cognitions towards the robot, $F(2, 18) = 3.93$, $p = 0.038$, partial $\eta^2 = 0.30$. Mauchly's Test of Sphericity indicated that the assumption of sphericity had not been violated in this test, $\chi^2(2) = 4.95$, $p = 0.08$. The linear test of within-subjects contrasts also demonstrated a significant relation between the independent, dependent and covariate variables, $F(1, 19) = 13.46$, $p = 0.002$, partial $\eta^2 = 0.42$. As anticipated, the negative cognitions decreased as the number of interactive social cues increased. These results demonstrate that the lowest negative cognitions were experienced by participants in the high number of interactive social cues condition ($M = 0.62$, $SD = 0.64$), followed by the interaction in low number of interactive social cues condition ($M = 1.00$, $SD = 1.20$) and the highest negative cognitions was recorded in no interactive social cue condition ($M = 1.38$, $SD = 1.15$). Using the Bonferroni post-hoc tests, pairwise comparisons revealed a significant difference in the mean negative cognitions scores only in the high number of interactive social cues and no interactive social cue conditions, $p = 0.02$. The score was 0.76 points lower for robot in high number of interactive social cues condition than the robot in no interactive social cue condition, with a 95% confidence interval [-1.36 -0.16]. However, no evidence of the effect of the number of interactive social cues on negative cognitions for other pairs were significantly differs (no interactive social cue vs low number of interactive social cues, mean difference of 0.38, $p = 0.26$) and (low number of interactive social cues vs high number of interactive social cues: mean difference of 0.38, $p = 0.08$).

In summary, psychological reactance, and specifically the measure of negative cognitions, was found to be lower when the robot has more interactive social cues.

Hypothesis 2: Compliance

A repeated measure ANCOVA test and linear test of within-subject contrasts revealed no statistically significant effect of the number of interactive social cues on compliance, $F(2, 18) = 0.81$, $p = 0.46$, partial $\eta^2 = 0.08$ and $F(1, 19) = 0.19$, $p = 0.67$, partial $\eta^2 = 0.01$ respectively. Thus, no conclusion can be made for the manipulation of the number of interactive social cues on compliance towards the persuasive robot.

Hypothesis 3: Trusting Beliefs

A repeated measure of ANCOVA test showed the influence of the number of interactive social cues was not significant on trusting beliefs, $F(2, 18) = 3.22$, $p = 0.06$, partial $\eta^2 = 0.26$. Mauchly's Test of Sphericity indicated that the assumption of sphericity had not been violated, $\chi^2(2) = 0.20$, $p = 0.90$. Confirming our hypothesis, the linear test of within-subjects contrasts also showed a significant relationship between the independent, dependent and covariate variables, $F(1,19) = 5.51$, $p = 0.03$, partial $\eta^2 = 0.23$. This linear relationship indicates that when participants interacted with the robot without social praises as the interactive social cues (in low number of interactive social cues condition), trusting beliefs were lower ($M = 3.29$, $SD = 7.38$) compared to the interaction with the robot that expressed social praises (in no interactive social cue: $M = 3.43$, $SD = 6.87$). As demonstrated in Figure 7.3, the highest trusting beliefs were reported in high number of interactive social cues condition, $M = 3.79$, $SD = 7.94$.

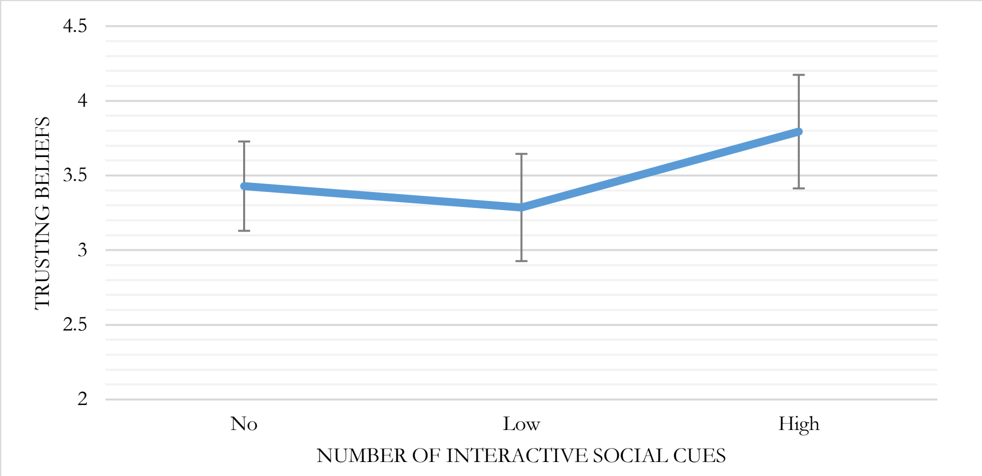

Figure 7.3: Mean and standard error trusting beliefs on persuasive robot scores by the number of interactive social cues. Participants reported the highest trusting beliefs on the persuasive robot in high number of interactive social cues condition and the lowest trusting beliefs for the persuasive robot in low number of interactive social cues condition.

In summary, these analyses reveal that persuasive robot with social praise enhances trusting beliefs towards the agent.

Hypothesis 4: Liking

We run a repeated measure ANCOVA with the number of interactive social cues of the robot as the independent variable, and liking score as the dependent variable. Results showed a significant main effect of the number of interactive social cues on liking, $F(2, 18) = 8.88$, $p = 0.002$, partial $\eta^2 = 0.50$ for which hypothesis 4 was accepted. Mauchly's Test of Sphericity indicated that the assumption of sphericity had not been violated, $\chi^2(2) = 1.74$, $p = 0.42$. Confirming our hypothesis, the linear test of within-subjects contrasts also showed a significant relationship between the independent, dependent and covariate variables, $F(1, 19) = 16.61$, $p = 0.001$, partial $\eta^2 = 0.47$.

As shown in Figure 7.4, results indicated that participants rated the robot in the high number of interactive social cues condition with the highest liking rate score ($M = 5.94$, $SD = 1.70$), followed by the robot in low number of interactive social cues condition ($M = 5.41$, $SD = 2.00$) and robot in no interactive social cues condition ($M = 5.01$, $SD = 1.78$). Using the Bonferroni post-hoc tests, the pairwise comparisons for the liking score for the robot in high number of interactive social cues and the robot in no interactive social cue conditions was significant, $p = 0.05$. The score was 0.93 points higher for the robot in high number of interactive social cues than for the robot in no interactive social cue, with a 95% confidence interval [-0.07, 1.88]. However, no evidence of the effect of the number of interactive social cues on liking rate for other pairs were significantly differs (low number of interactive social cues vs no interactive social cue, mean difference of 0.40, $p = 0.51$) and (high number of interactive social cues vs low number of interactive social cues: mean difference of 0.53, $p = 0.31$).

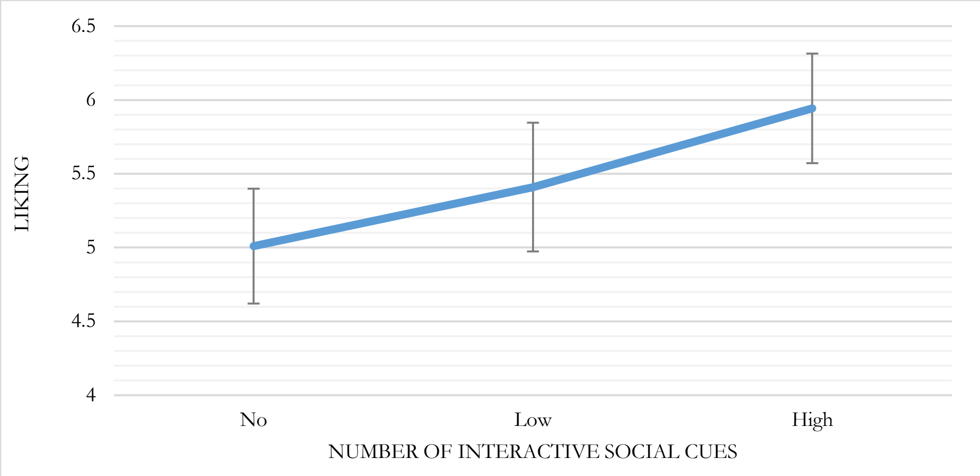

Figure 7.4: Mean and standard error of liking scores by the number of interactive social cues. Participants reported the highest liking score on the persuasive robot in high number of interactive social cues condition and the lowest liking score for the persuasive robot in no interactive social cue condition.

In summary, these analyses demonstrate clearly that liking of the persuasive robot increased with the increment of the number of interactive social cues it implements.

Hypothesis 5: Correlation between Psychological Reactance, Trusting Beliefs and Liking

With respect to the number of interactive social cues, Spearman's rho correlation coefficients were computed to assess the relationship between the significant dependent variables (psychological reactance, liking and trusting beliefs) that were involved in the previous hypotheses. Correlation of compliance on other dependent variables was not reported since we found no significant main effect of the number of interactive social cues on compliance. Results demonstrate first, strong negative correlations (2-tailed) between psychological reactance and liking with respect to the number of interactive social cues, $r_{no} = -0.90$, $p_{no} < 0.001$, $r_{low} = -0.91$, $p_{low} < 0.001$, and $r_{high} = -0.72$, $p_{high} < 0.001$. Second, moderate negative correlations were found between psychological reactance and trusting beliefs, $r_{no} = -0.63$, $p_{no} = 0.002$, $r_{low} = -0.45$, $p_{low} = 0.04$, and $r_{high} = -0.23$, $p_{high} = 0.32$. Third, moderate positive correlations were found between liking and trusting beliefs with respect to the number of interactive social cues, $r_{no} = 0.50$, $p_{no} = 0.02$, $r_{low} = 0.48$, $p_{low} = 0.03$, and $r_{high} = 0.51$, $p_{high} = 0.02$.

In summary, an increase in psychological reactance towards the persuasive robot was correlated with lower liking and lower trusting beliefs.

7.4 Discussion

In this study, we showed that interactive social cues that persuasive robot display (a social actor with strong social cues) influenced positive social responses in humans which is in line with Social Agency theory (Mayer et al., 2003). Findings from this study improves our understanding

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in designing social cues for persuasive robots so that the persuasive attempts by the robots on humans will be positively perceived by humans. This study also extends earlier research (Kaptein et al., 2011) in social psychology showing that interactive social cues (Verberne et al., 2013; Ham & Midden, 2014) have profound positive effects on humans in human-agent interactions. Importantly, the current research is the first investigation of the effects of the number of interactive social cues by persuasive robots on psychological reactance, compliance, trusting beliefs and liking in the context of the human-robot interaction.

Providing evidence for the first hypothesis, results showed that interactive social cues decreased the amount of psychological reactance experienced by the participants in persuasive attempts. Participants felt less reactance and had less negative cognitions when interacting with the robot that mimicked their head movements and praised them using the highes number of interactive social cues. Participants also reported the highest reactance when the robot displayed random head movements and random social praises during interaction in the no interactive social cue condition. Earlier research has indeed shown that proper timing of social praises enhanced the perception of the friendliness of a robot (Kaptein et al., 2011) while mimicry increased the social attractiveness of the mimicker (Adank et al., 2013) and facilitated negotiations (Fischer-Lokou, Guéguen, Lamy, Martin, & Bullock, 2014) in human-human interaction. Thus, less psychological reactance reported against the robot's persuasion in high number of interactive social cues condition compared to the robot that had random head movements and random social praises (vs low number of interactive social cues with head mimicry only). Findings regarding the first hypothesis indicate that the number of interactive social cues that a robot has is essential for the persuasion activity to invoke low reactance.

Related to hypothesis 2, we found no evidence of the effect of interactive social cues on compliance. This may be due to the limited number of choices given to the participants during the persuasive attempts (two choices in the first task selection and three choices in the second task selection) which did not appear to be enough to influence the participants to comply with the persuasive robot. An earlier study provides evidence that compliance towards persuasive agent can be enhanced by extending to the number of choices given in each task (Roubroeks et al., 2009).

In support of hypothesis 3, our results demonstrate the expected influence of interactive social cues on trusting beliefs only partly. That is, participants did not report higher trusting beliefs for the robot that mimicked their head movements (in low number of interactive social cues condition) than the robot that moves its head randomly and praises the participants at random moments (in no interactive social cue condition). However, as expected, participants reported higher trusting beliefs on the robot with head mimicry and interactive social praise (in high number of interactive social cues condition) than the robot with both random head movement and social praises (in no interactive social cue condition). These findings demonstrated that the participants had higher trusting beliefs towards the robot supporting social praise. Although the robot in no interactive social cue condition randomly praises the participants and some of the participants labelled them as a 'weird agent', people still choose to trust the 'weird' robot than the robot without any social praise like in the low number of interactive social cues condition. Thus, our study provided evidence that trusting belief in persuasive robots can be developed using social praise. This finding is in line with an earlier study (Li, Guo, Wang, & Zhang, 2016) that showed trusting beliefs was influenced positively by casual praise feedback in online product reviews. Apart from building trust using social praise, this study also showed that trusting beliefs towards the robot could be enhanced by combining social praise with head mimicry as used in high number of interactive social cues condition. This finding is in agreement with an earlier experimental study in evaluating the effect of a similar head mimicry (Verberne et al., 2013) an automotive setting using a non-embodied agent. Specifically, participants in that study trusted a 2D virtual agent more in the mimicked condition than the agent in the non-mimicked condition.

As expected in the fourth hypothesis, interactive social cues have a significant effect on liking towards the persuasive robot. This study showed that participants reported liking more the robot with the head mimicry and interactive social praises than the robot with the head mimicry only. They reported liking the least the robot with random head mimicry and random social praise. It can be suggested that the presence (no interactive social cues vs low number of interactive social cues) and the amount (low number of interactive social cues vs high number of interactive social cues) of interactive social cues are essential for persuasive robots to be liked by humans. Regarding head mimicry, this result is partly in line with research in social value orientation on the mimicry-liking link (Stel et al., 2011), which suggested that people with prosocial value orientation (people who take the well-being of others in considerations and seek for alternatives that maximize their own and other's well-being (McClintock, 1972) like to be mimicked than not being mimicked in human-human interaction. Liking the interaction partner, however, did not appear to be influenced by implementing mimicry for proself (people that oriented to maximized one's own well-being, either for competitiors or for the individualists (McClintock, 1972). Although the current research did not take into account participants' social value orientation, our study showed that head mimicry by the robot generally leads to liking, which is in line with earlier studies (Chartrand & Bargh, 1999; Verberne et al., 2013). Our result can also be explained by the findings highlighted in the earlier study (Chartrand & Lakin, 2013; Choi et al., 2017), in which perceived similarity is a strong predictor of liking. Humans like more robots that mimic them (see Duffy and Chartrand (2015)). Concerning interactive social praise, this study found positive effects of interactive social praise on liking which is similar to earlier findings (Strait, Canning, & Scheutz, 2014). Participants liked to interact with the robot that has delivers social praises at suitable moments compared to one offering random social praise. A possible explanation for this result could be that some participants reported they felt strange when the robot uttered random praise and they claimed that the compliments delivered by the robot were insincere and not genuine. This negative thought leads to liking the least the robot offering random praises in no interactive social cue condition than the robot with interactive praises in high number of interactive social cues condition.

Testing hypothesis 5 also showed that head mimicry and interactive social praise strengthened the effect of trusting beliefs and liking towards the persuasive robot as shown for the high interactive social cues condition and caused less psychological reactance after the persuasive attempts.

7.5 Summary

This chapter contributed to the scientific literature by extending our knowledge regarding the effects of the number of interactive social cues on persuasive robotics: (1) we have shown how head mimicry of a persuasive robot can lower psychological reactance and induce liking (2) we have illustrated how well timed social praise can lower psychological reactance and enhance liking (3) we have found that social praise even in random moments can increase trusting beliefs and (4) we have demonstrated how increasing the number of interactive social cues on a persuasive robot can lead to lower psychological reactance and higher liking. Finally (5) we have shown that low psychological reactance towards an agent was correlated with high liking and high trusting beliefs. From a practical standpoint, our results demonstrated how designing the persuasive robots with interactive social cues for example head mimicry and interactive social praises can lead to more positively perceived persuasion.

Despite the significant effects of social cues shown in earlier chapters on human social responses, we argue that social responses could be advantageous in predicting the acceptance of persuasive robots to be used in daily life. Accordingly, in the next part of the thesis, we explore the roles of social responses (psychological reactance, compliance, trusting beliefs and liking) to increase the power of prediction for the persuasive robots' acceptance.

PART III

ACCEPTANCE MODEL FOR PERSUASIVE ROBOTS

In this part, we investigate the roles of social responses within persuasive robots acceptance model. In Chapter 8, we conducted an experimental study to explain the acceptance of persuasive robots using Technology Acceptance Model (TAM). We also present Persuasive Robots Acceptance Model (PRAM), a new proposed acceptance model for persuasive robots by integrating TAM and social responses. Social responses included in PRAM are psychological reactance, compliance, trusting beliefs and liking. We aim to highlight the importance of considering social responses in evaluating human-robot interaction especially in persuasive attempts for better chances of acceptance.

CHAPTER 8

Persuasive Agents Acceptance Model: Roles of Social Responses within the Acceptance Model of Persuasive Robots

This chapter is based on an accepted paper:

Persuasive Robots Acceptance Model (PRAM): Roles of Social Responses within the Acceptance Model of Persuasive Robots (under review). *International Journal of Social Robotics*

Studies in Part 1 and Part 2 demonstrated the desirable *number* and *characteristics* of social cues so that the persuasive attempts will be effective (high compliance) and positively perceived (low psychological reactance, high trusting beliefs and high liking) by humans. Nevertheless, it is not yet understood to what extent people will accept to use robots as persuaders, nor is it clear how such factors may influence eventual acceptance. This chapter extends the technology acceptance model (TAM) by including measures of social responses to persuasive attempts. A laboratory experiment was conducted to evaluate user acceptance and social responses towards a persuasive robot in making decisions for donating to charities. The results were tabulated using the partial least squares (PLS) method showing that trusting beliefs and liking of the robot significantly add to the predictive power of the model regarding the acceptance of the persuasive robots. However, psychological reactance and compliance were not found to contribute to the prediction of acceptance.

8.1 Introduction

Louho, Kallioja, and Oittinen (2006) define technology acceptance as how people accept to adopt a specific technology for usage. Based on the theory of reasoned action (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975), Davis et al. (1989) designed the first technology acceptance model (original TAM) to explain people's acceptance of information systems and technology adoption. The original TAM predicted people's intention to use a technology by individuals based on several key determinants like perceived usefulness, perceived ease of use and attitude toward using. Subsequently, emphasizing social and cognitive factors such as sujective norms, demonstrability, voluntariness and experience as key determinants, TAM 2 (Venkatesh & Davis, 2000) aimed to predict user adoption behaviour towards systems used in organizations over time. Later on, a unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) was introduced to evaluate users' intentions to use *any* technology or information system in general. The key determinants in the UTAUT include performance and effort expectancies, social influence as well as facilitating conditions. Thereafter in 2008, the TAM 3 (Venkatesh & Bala, 2008) was developed to support decision making in organization by combining the key determinants from TAM 2 and introducing new determinants for perceived ease of use such as perceived enjoyment and computer anxiety. Eventually, UTAUT 2 (Venkatesh, Thong, & Xu, 2012) was introduced by adding hedonic motivation, price value and habit as determinants of acceptance and use, especially when predicting consumer behaviour.

UTAUT has been integrated with other acceptance models or frameworks for example integrations with task-technology fit (TTF) (Goodhue & Thompson, 1995) in Abbas et al. (2018) and Community of Inquiry (CoI) framework (Garrison, Anderson, & Archer, 1999) in Radovan and Kristl (2017). To date, UTAUT has been extended to evaluate the acceptance in other domains like in remote mobile payments (Slade, Dwivedi, Piercy, & Williams, 2015), acute care setting (Maillet, Mathieu, & Sicotte, 2015) and online purchasing tickets for low cost carriers (Escobar-Rodríguez & Carvajal-Trujillo, 2014). Similarly like UTAUT, TAM also has been integrated with other acceptance models in earlier studies for example integrations with Theory of Planned Behavior (TPB) (Ajzen, 1991) in Shima and Mohamadali (2017) and Innovation Diffusion Theory (IDT) (Rogers, 2003) in Hong, Shin, and Kang (2008). TAM also has been extended to evaluate the acceptance in other domains such as in e-learning system (Tarhini, Hone, Liu, & Tarhini, 2017), smart in-store technology (Kim, Lee, Mun, & Johnson, 2017) and internet banking adoption (Marakarkandy, Yajnik, & Dasgupta, 2017). To date, TAM has been applied to predict the acceptance of social robots (de Graaf, Ben Allouch, & van Dijk, 2017) in frontline service (Stock & Merkle, 2017), education (Conti, Di Nuovo, Buono, & Di Nuovo, 2017) and healthcare (Chen et al., 2017). Earlier research pointed out that social presence was one of the predictors in modelling the acceptance of robots in human-robot interaction (Lombard & Ditton, 1997). Others like Heerink et al. (2010a) claimed that social influence (Venkatesh et al., 2003) and trust were the key features for the acceptance of assistive social agents by elderly.

Earlier research informed us regarding social responses to persuasive robots such as psychological reactance, trust, rapport, and compliance (Ghazali, Ham, Barakova, & Markopoulos, 2018; Ghazali, Ham, Barakova, & Markopoulos, 2018; Herse et al., 2018; Lucas et al., 2018; Roubroeks et al., 2011; Siegel et al., 2009). In this study, we argue that social responses that persuasive attempts by a robot might invoke are also a key determinant for people to accept social technology like persuasive robots. That is, whether someone complies, or feels reactant towards a persuasive agent, are salient aspects of a persuasive interaction, and should shape the experience and the satisfaction by users. Examples of social responses may be to reject a robot that annoys people, to touch the robot or affective response such as engagement in the interaction with robots. Our earlier studies presented in Part 1 and Part 2 of the thesis demonstrated how social cues displayed by robots can influence the affective responses towards persuasive robots. Persuasive robots with minimal social cues for example, evoked less psychological reactance compared to persuasive robots with enhanced social cues in a decision-making game (cf. Chapter 5). Siegel et al. (2009) found that persuasive robots with opposite gender than the users were experienced as more trustworthy and engaging compared to the similar gender robots in a donation task. Ham and Midden (2014) provided evidence that people complied more with persuasive robots that provided negative feedbacks in promoting energy saving behaviour than the same robots with positive feedbacks. However, these studies do not yet help us to gain a higher level understanding of whether and to what extent social responses like psychological reactance and compliance can determine whether people *accept* robots as persuasive agents.

We proposed to extend the existing TAM with the evaluation of social responses towards the robot by measuring users' psychological reactance, compliance, trusting beliefs and liking. In this chapter, we reported an experiment that used SociBot as a persuasive robot in a decision-making game. The following sections described the methods used and elaborated the results of our study. We concluded discussing the implications of social responses for the development of TAM for social robots in general and for persuasive robots in specific.

The Current Study

This study investigated the acceptance of persuasive robots using all key determinants from the original TAM (Davis et al., 1989) and a key determinant from TAM 3, that is, perceived enjoyment (Venkatesh & Bala, 2008). TAM is considered as the most popular acceptance model and is widely used in several fields due to its parsimony and specificity in predicting acceptance for diverse populations of users, strong theoretical base, and strong empirical support for its exploratory power (de Graaf et al., 2017; Yousafzai, Foxall, & Pallister, 2007). We used TAM instead of UTAUT as the basis for our model since UTAUT models (Venkatesh et al., 2003; Venkatesh et al., 2012) require a large number of key determinants and moderators (e.g., up to forty-one variables to predict intentions) (Bagozzi, 2007) in attaining high reliability of prediction (Van Raaij & Schepers, 2008). Thus, UTAUT models (Venkatesh et al., 2003; Venkatesh et al., 2012) suffer from huge numbers of key determinants which later require a big sample size in testing the model. To retain the simplicity of our proposed model, we selected the key determinants of the original TAM (Davis et al., 1989) and a key determinant from TAM 3 (Venkatesh & Bala, 2008). This has been done since several key determinants from social responses will also need to be integrated in the model for testing. More importantly, most of the additional key determinants in TAM 2 (Venkatesh & Davis, 2000) and TAM 3 (Venkatesh & Bala, 2008) (compared to the original TAM (Davis et al., 1989)) are not very relevant for the acceptance and use of persuasive robots. Thereby, measuring output quality and self-efficacy (examples of key determinants in TAM 3 (Venkatesh & Bala, 2008)) are out of our research interests. However, we included the variable of perceived enjoyment from TAM 3 (Venkatesh & Bala, 2008) in our model since enjoyment is a type of social response.

Earlier works (Admoni & Scassellati, 2017; Breazeal et al., 2018; Goble & Edwards, 2018) reported both positive and negative responses to social cues in robots. Perhaps counter intuitively, our studies reported in earlier chapters suggested that persuasive robots were more effective when endowed with only minimal social cues such as eye-blinking rather than implementing several cues at once, e.g., combining emotional intonation voice, head movement and facial expression. Further, it has been shown that persuasive robots should be designed with likeable social features such as having a neutral face (less expressive) and facial characteristics that were known to evoke trust (see Todorov and Oosterhof (2011)). Additionally, the robot should mimic humans head's movement, and praise humans only at appropriate times during interaction (Kaptein et al., 2011). Such social cues contributed to positive social responses toward persuasive robot namely low psychological reactance, high compliance, high trusting beliefs and /or high liking. While such social responses have been demonstrated experimentally, it was not yet clear what their importance is with regards to whether people will be prepared to adopt social robots as persuasive agents i.e. we did not know if people will be more likely to use a robot they trust more, they like more and that will make them feel less reactant as a persuasive agent.

Using the social cues that were found to be positively perceived by humans in the earlier studies, this study mainly aimed to extend the technology acceptance (TAM) to account for the influence of social responses onwards the persuasive robot. This study was developed to:

Obj1 Propose an explanation of the acceptance of persuasive robots

We used the framework of TAM as a basis in this study to explain the acceptance of persuasive robots. Earlier research (Marangunić & Granić, 2015) in social robotics (Chen et al., 2017; De Graaf, Allouch, & Klamer, 2015; Heerink et al., 2010a) utilized measurements from TAM in understanding the acceptance of robots for daily usage. The key determinants taken from TAM include *Usefulness*, *Ease*, *Attitude* and *Intentions* originated from original TAM (Davis et al., 1989) and *Enjoy* from TAM 3 (Venkatesh & Bala, 2008).

Within the context of our experiment, *Usefulness* is defined as the degree to which people believe that the persuasive robots would be assistive in making decisions (Davis, 1989). The term *Ease* refers to the degree to which people believe that using the technology (i.e., the persuasive robot) would be free of effort (Davis, 1989). Whereas *Attitude* covers the user's feelings (evaluative affect) about the technology (in this study the persuasive robot) (Davis, 1989) while *Intentions* refer to the strength of people's intention about using the persuasive robots (Davis, 1989). *Enjoy* can be defined as the pleasant feelings associated with the use of the persuasive robots, apart from the (positive) performance consequences (Davis, Bagozzi, & Warshaw, 1992). Based on the original TAM (Davis, 1989; Davis et al., 1989), we expected that *Usefulness* is a determinant of *Attitude* and *Intentions*, *Ease* is a determinant of *Attitude*, and *Attitude* is a determinant of *Intentions*. Based on the prediction in TAM 3 (Venkatesh & Bala, 2008), *Enjoy* is a determinant of *Ease*.

Obj2 Extend technology acceptance model to account for social responses to persuasive robots

We suggested adding four key determinants to represent social responses within the PAAM to increase the power of prediction for the persuasive robots' acceptance. The key determinants include *Compliance, Beliefs, Reactance* and *Liking*, because of the arguments presented below in this section.

Compliance is a trust measure known as trusting behaviours (Schlosser, White, & Lloyd, 2006) calculated based on observation as in earlier studies. The compliance score in the current study was calculated by how many times participants complied with the advice given by the persuasive robot. For instance, if a particular participant follows the advice given by the persuasive robot to donate the €1 to certain charity organizations in three specific tasks in our experiment, while making their own decisions by ignoring the advice in two other tasks, then the participant would be granted *Compliance* score of 3. Although there was no clear relation of *Compliance* with the key determinants of TAM in earlier studies especially on the acceptance of persuasive robots, Kelman (1958) highlighted that *Compliance* can be predicted by *Attitude* in the process of adopting induced behaviour; although this study was performed in a different domain (desegregation in public schools). In this work, we are interested in investigating whether social responses like *Compliance* are a key determinant for people to *accept* robots as persuasive agents. Relatedly, we investigate whether (as the first hypothesis contained in PAAM) a user's *Compliance* predicts his or her *Attitude* and *Intentions* (Warkentin et al., 2011) to use the system in the future.

Scholars like McKnight et al. (1998) explained that the concept of trust consists of several elements, including trusting beliefs (*Beliefs*) and trusting behaviours (*Compliance*). Vidotto et al. (2012) elaborated trusting beliefs as a modulator in inducing people to believe that someone else (in our case the persuasive robot) can be trusted (McKnight et al., 1998). *Beliefs* have been empirically established as a determinant of *Usefulness* and *Attitude* in earlier studies (Chauhan, 2015; Ha & Stoel, 2009; Pavlou, 2003). In addition, our studies in Part 2 demonstrated a negative correlation between *Beliefs* and *Reactance*. That is, participants who have more trust in the robot will experience less reactance in following the advice given by the robot. Therefore, it was predicted in our second hypothesis that *Beliefs* on the persuasive robot will cause people to think that the robot is able to provide the best advice in selecting the charity organizations (*Usefulness*), causing them to comply more with the advice given (*Compliance*) with positive *Attitude* and show less psychological reactance (*Reactance*).

Liking describes the extent to which people feel friendly, kindly disposed and nice towards robots (Mileounis, Cuijpers, & Barakova, 2015). Although there has been no prior study directly investigating the effect of *Liking* on *Intentions* in persuasion domain, earlier work (Venkatesh et al., 2003) illustrated that *Liking* is an example of intrinsic motivation associated with technology usage based on Cognitive Evaluation Theory (Deci & Ryan, 1985). A more recent study by Kim et al. (2007) has shown that behavioural intentions (*Intentions*) in using mobile internet can be influenced by intrinsic motivation. Thus, in our third hypothesis, we expected that *Liking* is one of the determinants of *Intentions*. Other researchers (Cialdini & Cialdini, 2007; Rains & Turner, 2007) report that *Liking* towards a persuasive robot is positively correlated with *Beliefs* and negatively correlated with *Reactance*. That is, participants who like the robot more will have more trust in it, experience less reactance to follow the advice given, and have more intentions to use the robot again in the future. Chapter 6 of the thesis investigating psychological reactance showed that *Liking* is a full mediator between facial characteristics of a social robot (an independent variable) on *Beliefs* and *Reactance*. Thus, it is anticipated that *Liking* is more likely to influence the level of *Beliefs* and *Reactance* in this study.

In a model of sustainable energy technology acceptance, Huijts et al. (2012) highlighted that negative feelings like anger, fear and worries influence the *Attitude* towards using novel technologies. A similar concept of negative attitudes, psychological reactance (*Reactance*), was introduced earlier by Brehm (1966), and has been elaborated in several studies (Dillard & Shen, 2005; Ehrenbrink & Prezenski, 2017; Quick, Kam, Morgan, Montero Liberona, & Smith, 2015; Roubroeks et al., 2011). Based on the implication of negative feelings on *Attitude* (Huijts et al., 2012) and earlier research investigating psychological reactance (Dillard & Shen, 2005; Ehrenbrink & Prezenski, 2017; Quick et al., 2015; Roubroeks et al., 2011), the fourth hypothesis predicts that *Reactance* determines *Attitude* in technology acceptance model for the persuasive robot.

As described in an earlier study (Bruner II & Kumar, 2005), it was expected in the fifth hypothesis that people will like (*Liking*) the persuasive robot more if the robot is easy to be used, compared to the robots that are cumbersome to use, or even later caused frustration. Thus, it was predicted in the fifth hypothesis that *Ease* is a determinant of *Liking* towards the persuasive robot.

As proposed by the Cognitive Evaluation Theory (Deci & Ryan, 1985), perceived enjoyment *(Enjoy)* is one of the intrinsic motivations next to *Liking*. Thus, similar to *Liking*, we expect that *Enjoy* is a determinant of *Intentions* (Kim et al., 2007). This expectation is in line with flow theory (Ghani, 1995). Also, based on earlier research of the acceptance of instant messaging technology (Lu et al., 2009) which combines the theory of planned behavior (Ajzen, 1991), TAM (Davis et al., 1989), and flow theory (Ghani, 1995), we hypothesize that *Enjoy* is a determinant of *Attitude* and *Intentions*.

In summary (refer to Figure 8.1), when developing the PAAM, we hypothesized that:

H1. **Compliance**

H1(a). There is a significant difference in attitude towards using the robot between participants who comply more with the request made by the robot and those who comply less with the request made by the robot

H1(b). There is a significant difference in intentions to use the robot again in the future between participants who comply more with the request made by the robot and those who comply less with the request made by the robot

H2. **Trusting beliefs**

H2(a). There is a significant difference in reactance score between participants who have more trust on the robot and those who have less trust on the robot

H2(b). There is a significant difference in perceived usefulness score between participants who have more trust on the robot and those who have less trust on the robot

H2(c). There is a significant difference in attitude towards using the robot between participants who have more trust on the robot and those who have less trust on the robot

H2(d). There is a significant difference in compliance score between participants who have more trust on the robot and those who have less trust on the robot

H3. **Liking**

H3(a). There is a significant difference in trusting beliefs score between participants who like the robot more and those who like the robot less

H3(b). There is a significant difference in reactance score between participants who like the robot more and those who like the robot less

H3(c). There is a significant difference in intentions to use the robot again in the future between participants who like the robot more and those who like the robot less

H4. **Psychological reactance**

H4(a). There is a significant difference in attitude towards using the robot between participants who experience less reactance and those who experience more reactance

H5. **Ease of use**

H5(a). There is a significant difference in liking score between participants who find the robot easy to use and those who find the robot hard to use

H6. **Enjoyment**

H6(a). There is a significant difference in liking score between participants who enjoy using the robot more and those who enjoy using the robot less

H6(b). There is a significant difference in attitude towards using the robot between participants who enjoy using the robot more and those who enjoy using the robot less

H6(c). There is a significant difference in intentions to use the robot again in the future between participants who enjoy using the robot more and those who enjoy using the robot less

Obj3 Compare the predictive power in explaining the acceptance of the persuasive robots using technology acceptance model and the PAAM

To determine whether the prediction of behavioural intentions (*Intentions*) in using the persuasive robots can be improved by the inclusion of social responses (*Reactance*, *Beliefs*, *Compliance* and *Liking*).

8.2 Materials and Methods

8.2.1 Participants

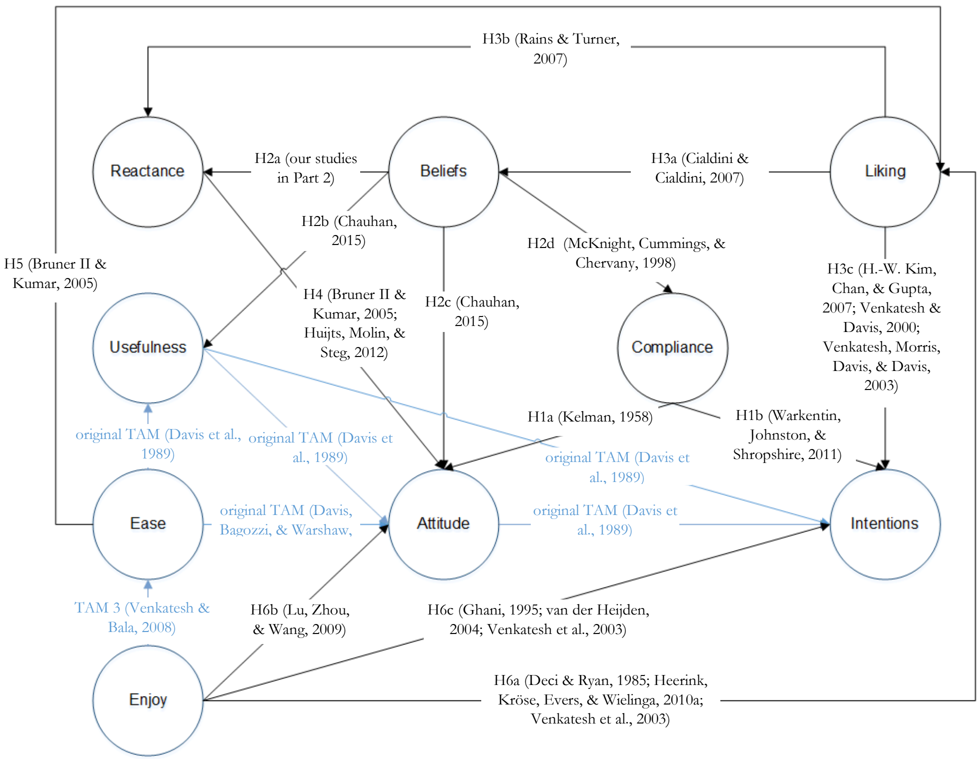
Seventy-eight participants (41 males and 37 females) were recruited with ages ranging between 19 and 52 (M = 26.949, SD = 6.524). The experiments lasted 45 minutes for which participants were given a €7.5 voucher for university students or staff and extra €2 for external participants as a token of appreciation. The participants were required to meet the inclusion criteria: Normal colour vision and fit for a simple exercise. Participants were randomly selected from a local participant database with no restriction of age, gender and nationality.

8.2.2 Persuasive Robot

As in the our earlier experiments, we used SociBot as a persuasive agent with a facial image of a man with hazel eyes and light brown skin colour tone to minimize the psychological reactance towards the persuasive robots (cf. Chapter 6). Using the Wizard-of-Oz technique (Kelley, 1984), the advice by the SociBot was controlled by the experimenter in a control area adjacent to the experiment locale. This technique was used to enforce proper timing of responses from SociBot during the interaction. That is, the experimenter controlled the sequence of dialogues delivered by the SociBot based on the actions of the participants. For example, the SociBot acknowledged the decision made by the participant (e.g., '*Thank you for your selection*') only after the participant showed the selected envelope in front of the robot's camera).

8.2.3 Task

SociBot was used as a robotic advisor to guide participants in performing two activities. In the first activity, the participants were required to do a simple one-minute weight shifting exercise. Instructed by the robot, the participants were asked to move their body left and right for two times, each side approximately for three seconds. A manual for this exercise was placed on the right-hand side of the experimental table (see Figure 8.2). This first activity was designed to increase the participants' awareness towards the robot capability in mimicking the participants' head movements.



Notes: Reactance= Psychological reactance, Beliefs= Trusting beliefs, Usefulness= Perceived usefulness, Ease= Perceived ease of use, Enjoy= Perceived enjoyment, Attitude= Attitude towards using, Intentions= Behavioural intentions

Figure 8.1: Hypotheses for PAAM.

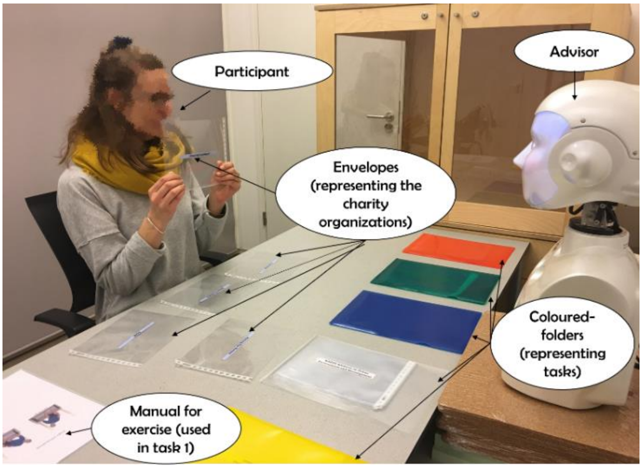


Figure 8.2: Experimental set ups.

Persuasive attempts by the robot only started in the second activity. For the second activity, the participants were asked to make several decisions for donating money to charities. Five coins with €1 value were placed in front of the participants. In this experiment, the participants have to allocate those euros to one of five charity organizations in each task. In five tasks, the participants were presented with different charity organizations in five different colours of folders. For example, in the first task, several animal charity organizations were presented in the red colour folder. The participants had to choose and give one of these animal charity organizations €1.

So, generally, in each of the five tasks, the participants chose one charity organization to which they decided to give the €1. In each task, the robot will introduce the charity organizations. Then, the robot will advise the participants to which of these to give the €1. As emphasized by the experimenter and the robot, the participants can choose either to follow the robot advice (donate the €1 to the charity that suggested) or to make their own selection by choosing one of the other charities listed (ignore the advice). The experimenter and the robot emphasized that there is no right or wrong answer in this donation task before the experiment started. In the folder of each task, there are envelopes representing the charity organizations. The participants simply selected a charity organization by putting the €1 coin into the charity organization's envelope.

The participants were told that this experiment involves real money and real choices. That is, the total of €5 coins donated by them in five tasks would actually be paid afterwards to the selected charity organizations by the experimenter. This was done to increase the ecological validity of the choice behavior and to ensure involvement by participants. The latter have been found to be important in earlier studies (see Chapter 4 and Oreg and Sverdlik (2014)). In avoiding the participants to donate the money based on their personal preferences, we kept the identity of the charity organizations as ambiguous as possible by only putting the initial for the charity organizations on the envelope. This is important since diverse attitudes may exist among participants and persuasive communication can make a difference if they have their own preferences.

8.2.4 Procedure

Each participant was greeted upon arrival and sat on a chair facing the robot (see Figure 8.2). A laptop was placed near to the participant, for filling in the pre and post experiment questionnaires. An Internet Protocol (IP) camera was attached near to the robot to record the activities during the experimental session. This experiment consisted in three phases: (1) Introduction [10 minutes] (2) Experiment [20 minutes] (3) Closing [15 minutes]

In the first phase, the participant read and signed a consent form. After that, the experimenter summarized the experimental procedure and demonstrated how to do the exercise and donate the money. The experimenter left the experimental room after asking the participant to fill in their demographic information using laptop provided.

The second phase started as the robot introduced itself after detecting the participant's face. During this phase, the participant was asked first to do a simple physical exercise as explained earlier. The robot praised the participant at the end of the first activity only if the participant had done the instructed exercise by saying '*Good job!*' Next, the robot introduced the first decision task for the donation, for the first charity organization (e.g., animal charity organization). The participant was asked to take a specific colour folder (e.g., green folder) and take a look at the envelopes with the names of animal charity organizations inside that folder. After that, the robot would provide an advice to the participant by asking him/her to donate the €1 coin to a specific charity. After making up his/ her mind to which charity the participant wished to donate the money, the participants were required to put the €1 coin in the selected charity's envelope and show the envelope to the robot for a record. The robot would praise the participant's selection in case the participant chose to donate the money to the charity suggested by the robot. Examples of the social praise are *'Thank you, it is a wise selection'* and '*Nice, I like your choice.'* Alternatively, the robot will acknowledge the selection made by saying '*I acknowledge your decision'*. Highly coercive language was used during the persuasive attempts for higher chances of compliance as demonstrated in the earlier study (cf. Chapter 3), e.g., '*You **have to** select the <charity A> to donate the €1 for the animal charity organizations*' and '***Definitely**, you **need to** donate the €1 to the <charity A>*'.

After completing all donation tasks, the robot asked the participant to fill in the post session questionnaire on the laptop provided in the third phase of the experiment. The participant was debriefed by the experimenter in oral form and received a small monetary reward or research credits for the participation at the end of the experiment as detailed above.

8.2.5 Measures

Questionnaires for measuring the TAM constructs were adapted from scales used in earlier technology acceptance studies. We used the same social responses questionnaires as in the studies reported in the previous chapter to measure psychological reactance, trusting beliefs and liking of the robot. The phrasing of the questionnaires was adapted to the content of our study especially the specific technology under investigation (persuasive robots) while preserving the essence of the questions (see Table 8.1). Each measure that overlaps between constructs was asked only once. The question items assessing the psychological constructs measured using our questionnaires have been calculated in this study and were shown to have high internal reliability (see high Cronbach's α values reported below).

Table 8.1: Scales used to assess the constructs of the tested model.

Usefulness [a] By using this robotic advisor... **Use1.** I can decide more quickly and easily to which charity I want to donate than without using this robotic advisor **Use2.** I can better decide to which charity I want to donate than without using this robotic advisor **Use3.** I am better informed about the suggested charities **Use4.** I can decide more quickly and more easily whether I want to donate the money to the suggested charity or not **Use5.** I can better decide whether I want to donate the money to the suggested charity or not Sources: All Use items were adapted from a study by van der Heijden (2004) in the acceptance of hedonic information system. Cronbach's α = 0.86.
Ease [a] **Ease1.** Interaction with this robotic advisor is clear and understandable **Ease2.** Interaction with this robotic advisor does not require a lot of mental effort **Ease3.** I find it is easy to use this robotic advisor **Ease4.** I believe that the use of this robotic advisor is trouble-free Sources: All Ease items were adapted from a study by Venkatesh (2008) studying TAM 3. Following Chauhan (2015), we replaced the fourth item of Perceived Ease of Use (PEOU4: I find it easy to get the system to do what I want it to do) from TAM 3 (Venkatesh (2008)) by the current Ease 4 item, slightly rephrasing it to fit the current context. Cronbach's α = 0.72.
Attitude [a] **Att1.** I have a favourable attitude towards using this robotic advisor **Att2.** I like the idea of providing information about the charities through this robotic advisor **Att3.** I believe that this robotic advisor is beneficial in improving my decision **Att4.** Using this robotic advisor to improve my knowledge about the charities would be a good idea Sources: Att1 and Att2 were adapted from a study by Davis, Bagozzi, and Warshaw (1989); Att3 and Att4 were adapted from a study by Chen et al. (2017) in the acceptance of robot for partner dance-based exercise. Cronbach's α = 0.88.

Intentions [a] Assuming I have access to this robotic advisor again… **Int1.** I would intend to use it **Int2.** I predict that I would use it **Int3.** I would certainly use it **Int4.** I would say something favourable about this robotic advisor Sources: Int1 and Int2 were adapted from a study by Venkatesh (2008) in TAM 3 (Venkatesh & Bala, 2008); Int3 and Int4 were adapted from a study by Chauhan (2015) in the acceptance of mobile money. Cronbach's α = 0.94.
Enjoy [a] **Enjoy1.** I would find using this robotic advisor to be enjoyable **Enjoy2.** I would find using this robotic advisor to be fun **Enjoy3.** I would find using this robotic advisor to be entertaining **Enjoy4.** I would find using this robotic advisor to be exciting Sources: Enjoy1 and Enjoy2 were adapted from a study by Venkatesh (2008) in TAM 3 (Venkatesh & Bala, 2008); Enjoy3 and Enjoy4 were adapted from a study by Chen et. al (2017). Cronbach's α = 0.91.
Reactance [b] **Reac1.** I feel irritated towards this robotic advisor [b] **Reac2.** I feel angry towards this robotic advisor [b] **Reac3.** I feel annoyed towards this robotic advisor [b] **Reac4.** I feel aggravated towards this robotic advisor [c] **React5.** Please report all the thought you had while receiving the advice from this robotic advisor, even those thoughts had nothing to do with the advice. Then, please indicate for all thoughts whether it is positive (P), neutral (Neu) or negative (N) thought. Sources: All Reac items (except Reac5) were adapted from studies by Dillard and Peck (2000) and Dillard et al. (1996); React5 were adapted from a study by Dillard and Shen (2005) using cognition scale developed by Shaver et al. (1987). Cronbach's α = 0.86.

Liking [a] This robotic advisor was… **Like1.** approachable **Like2.** confident **Like3.** likeable **Like4.** trustworthy **Like5.** interesting **Like6.** friendly **Like7.** sincere **Like8.** warm **Like9.** competent **Like10.** informed **Like11.** credible **Like12.** modest **Like13.** honest Sources: All Like items were adapted from a study by Verberne, Ham and Midden (2015) (F. M. Verberne et al., 2015) on measuring liking towards an artificial social agent as an interaction partner, also from a study by Guadagno and Cialdini (2002). Cronbach's $\alpha = 0.88$.
Beliefs [a] **Bel1.** This robotic advisor behaves in an ethical manner **Bel2.** I am confident of the intentions, actions, and outputs of this robotic advisor **Bel3.** I am not wary of this robotic advisor **Bel4.** I am confident with this robotic advisor **Bel5.** I will trust this robotic advisor if it gives me advice again in the future **Bel6.** I trust that this robotic advisor can provide me with the best advice **Bel7.** I will follow the advice that this robotic advisor gives me Sources: Bel1 to Bel4 were adapted from a study by Jian et al. (2000); Bel4 to Bel7 were adapted from studies by Heerink et al. (2009) and Tay et al. (2014). Cronbach's $\alpha = 0.89$.

Notes: a. 7-point Likert scale, ranging from completely disagree (1) to completely agree (7)
b. 5-point Likert scale, ranging from completely disagree (1) to completely agree (5)
c. Open-ended question

8.3 Findings

We used SmartPLS version 3.2.7 to estimate the validity of the TAM and PAAM using partial least square (PLS) path modelling method (Ringle, Wende, & Becker, 2015). Instead of evaluating covariance of the variables (like in AMOS, Stata etc.), SmartPLS uses variance values to identify the relationship between key determinants (or known as latent variables in PLS terms) (Bagozzi & Yi, 2012; Henseler, Ringle, & Sinkovics, 2009). We chose SmartPLS since it is suitable for non-normally distributed data (as we found that some of our latent variables were skewed and have kurtosis: see Table 8.2) and small sample sizes (less than 200). Additionally, SmartPLS is good at handling a large number of indicators (Hair, Sarstedt, Ringle, & Mena, 2012).

8.3.1 Preliminary Analysis

We searched for outliers in the data and show that there are none. The descriptive statistics for the latent variables used in this study are shown in Table 8.2.

Table 8.2: Descriptive statistics.

Construct	*M*	*SD*	*Skewness*	*Kurtosis*
Reactance	1.02	0.56	3.62	0.37
Beliefs	4.31	1.12	0.01	-0.46
Compliance	3.12	1.07	-0.30	-1.23
Liking	4.92	0.76	-0.01	-1.12
Usefulness	4.61	1.23	-1.28	-0.07
Ease	5.91	0.76	-3.11	1.17
Enjoy	4.95	1.13	-1.51	0.61
Attitude	5.01	1.26	-2.19	0.19
Intentions	4.71	1.49	-1.72	-0.99

According to George (2011), the acceptable range for skewness and kurtosis are ±1.96. It is demonstrated in Table 8.2 that *Reactance*, *Ease*, and *Attitude* strayed from a normal distribution.

To check the potential effects of participants' age and gender on the constructs, two Multivariate Analysis of Variance (MANOVA) tests were conducted on *Usefulness, Enjoy, Intentions, Beliefs, Liking* and *Compliance*. Results showed that 1) no significant effect of age and 2) no significant effect of gender on the stated dependent variables. For the non-parametric constructs, Kruskal-Wallis H test showed that there was no statistically significant difference in age [1] and gender [2] on *Ease* and *Attitude*. Additionally, the Kruskal-Wallis H test was conducted to check the main effect of participants' age and gender on *Reactance* (feelings of anger and negative cognitions). As expected, we found that 1) no significant effect of age, $\chi^2(2) = 17.84$, $p = 0.72$ and 2) no significant effect of gender, $\chi^2(2) = 2.41$, $p = 0.12$ on *Reactance* (see Table 8.3).

The 2-tailed Pearson correlation between feelings of anger and negative cognitions (elements for *Reactance*) is 0.28, $p = 0.02$. In line with the proposed conceptualization of reactance (Dillard & Shen, 2005), our results showed that feelings of anger and negative cognitions were correlated. Results implied an overlap between the *Reactance* constructs. Thus, to test the hypotheses in the PAAM, the reactance score (*Reactance*) for each participant was calculated by averaging the participant's score on feelings of anger and negative cognitions.

8.3.2 Objective 1

The first aim of this study was to verify that the technology acceptance model (TAM) can be employed to explain and predict the acceptance of persuasive robots. This model composed of five latent variables as *Usefulness*, *Ease*, *Enjoy*, *Attitude* and *Intentions*.

[1] Main effect of age on (a) *Ease*, $\chi^2(2) = 21.68$, $p = 048$ (b) *Attitude*, $\chi^2(2) = 25.01$, $p = 0.30$
[2] Main effect of gender on (a) *Ease*, $\chi^2(2) = 0.24$, $p = 0.62$ (b) *Attitude*, $\chi^2(2) = 0.12$, $p = 0.89$

Table 8.3: Main effect of (a) age (b) gender on constructs.

Construct(s)	***F*(22, 55)**	***p***	***F*(22, 55)**	***p***
	Main effect of **age** on		Main effect of **gender** on	
(a) Usefulness	1.11	0.37	0.40	0.53
(c) Enjoy	1.06	0.41	0.32	0.57
(e) Intentions	1.72	0.054	0.32	0.57
(f) Beliefs	1.22	0.27	0.01	0.93
(g) Liking	1.04	0.43	0.72	0.40
(h) Compliance	1.13	0.35	0.02	0.88

Psychometric properties of the TAM

We ran confirmatory factor analysis to observe the reliability and validity of the data by examining how well the measured observed variables represent the latent variables (Hair, Black, Babin, Anderson, & Tatham, 1998). The analysis includes measuring Average Variance Extracted (AVE), reliability (Cronbach's α), Composite Reliability (CR), Discriminant Validity (DV), and collinearity (Bilgihan, 2016).

Average Variance Extracted (AVE)

AVE reflects the number of observed variables correlated with their respective latent variables due to measurement errors (Ringle, Da Silva, & Bido, 2015). In observing the convergent validities, the AVE for each latent variable, that is the mean of factor loading square, should be bigger than 0.50 (AVE > 0.50) (Fornell & Larcker, 1981; Henseler et al., 2009). Results showed that the AVE for all latent variables was higher than 0.50. Thus, convergent validity was established.

Composite Reliability (CR)

We ran a reliability analysis by observing the internal consistency values (known as Cronbach's *a*) and the overall reliability of the latent variables by assessing the standardized loading, error variance, and R^2 values of each observed variables (Bacon, Sauer, & Young, 1995; Fornell & Larcker, 1981; Ringle, Da Silva, et al., 2015). The values for both Cronbach's *a* and CR should be equal to or greater than 0.70 to be considered as adequate (Fornell & Larcker, 1981; Nunnally, Bernstein, & Berge, 1967). Without eliminating any observed variables, the Cronbach's *a* and CR for all latent variables were higher than 0.70.

Discriminant Validity (DV)

We used discriminant validity as an indicator to ensure that all latent variables are independent of one another (Henseler, Ringle, & Sarstedt, 2015). That is, the factorial loads of the observed variables for a latent variable must be greater than the factorial loads to the other latent variables (Ringle, Da Silva, et al., 2015). According to Fornell-Larcker Criterion (Fornell & Larcker, 1981), the convergent validity of the measurement model can be assessed by the AVE and CR. Applying this criterion, we confirmed the discriminant validity of our data.

Collinearity Statistics (VIF)

The collinearity of the latent variables was observed by using variance inflation factor (VIF). Ringle et al. (2015) stated that the maximum value of VIF should be '5.00' in avoiding multicollinearity issues. VIF for our data showed excellent results, presenting in all cases values lower than 2.00.

Evaluation of the TAM

The acceptance of persuasive robot using TAM was tested by examining the significance level (t-test) (Henseler & Sarstedt, 2013) using bootstrapping (Chin, 1998) with 1000 subsamples (as recommended by Hair Jr, Hult, Ringle, and Sarstedt (2016)). f^2 (Cohen's Indicator) value was used to reflect the effect size of each predictor in explaining the predicted variable (Cohen, 1988). Hair Jr et al. (2016) suggested that the Cohen's effect size values of 0.02, 0.15, and 0.35 are considered as small, medium, and large effect respectively.

We found a medium effect of *Ease* in predicting *Attitude* (f^2 = 0.21) and *Usefulness* (f^2 = 0.220), and *Enjoy* in predicting *Ease* (f^2 = 0.30). Results also showed a large effect of *Attitude* in predicting *Intentions* (f^2 = 1.36) and *Usefulness* in predicting *Attitude* (f^2 = 0.43). Results presented in Figure 8.3 showed that almost all paths (except for the prediction of *Intentions* by *Usefulness*) were statistically significant. Path coefficient for each prediction was also observed in this analysis.

For a global view of the TAM, results demonstrated a satisfactory R^2 of 0.52 for *Attitude*, and high R^2 of 0.73 for *Intentions*.

As expected from the insignificant path of *Usefulness* in predicting *Intentions*, no effect (f^2 = 0.02) was found on the mentioned latent variables. We used regression analysis to investigate whether *Attitude* mediated the effect of *Usefulness* on *Intentions*. First, this analysis showed that *Usefulness* was a significant predictor of *Intentions* (B = 0.68, SD = 0.96), t = 6.24, F(1, 76) = 38.93 (path c). Second, we checked for a positive relationship between *Usefulness* and *Attitude*. Results confirmed that *Usefulness* was a significant predictor of *Attitude* (B = 0.62, SD = 0.80), t = 6.92, F(1, 76) = 47.90 (path a). Third, we checked whether the suspected mediator (*Attitude*) affect the outcome (*Intentions*). Indeed, *Attitude* was a significant predictor of *Intentions* (B = 0.85, SD = 0.63), t = 13.86, F(1, 76) = 191.99 (path b). Finally, this analysis showed that the effect of *Usefulness* on *Intentions* became non-significant when taking into account *Attitude* in the regression analysis (B = 0.09, SD = 0.80), t = 1.17, F(2, 75) = 97.14 (path c'). These results support the hypothesis that *Attitude* was a full mediator of the relationship between the *Usefulness* and *Intentions*.

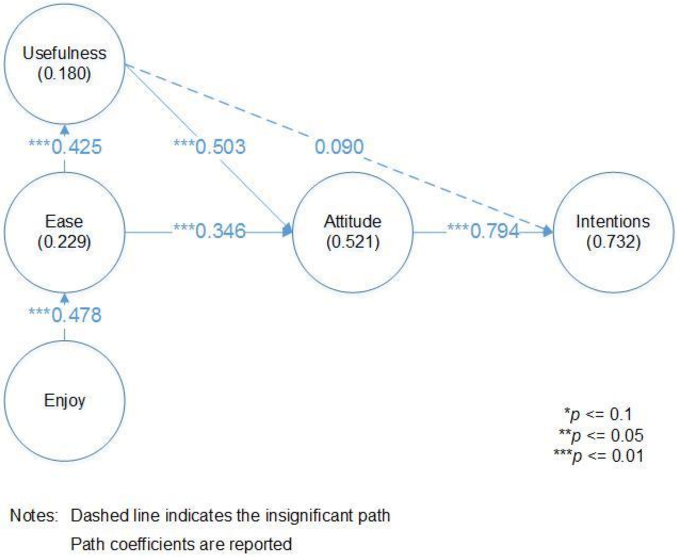


Figure 8.3: SEM using TAM.

8.3.3 Objective 2

The second goal of this study was to describe the acceptance of persuasive robots using a proposed model called Persuasive Agents Acceptance Model (PAAM), by incorporating the technology acceptance models (original TAM (Davis et al., 1989) and TAM3 (Venkatesh & Bala, 2008)) and social responses factors. The PAAM consisted of ten latent variables. Latent variables that stem from the TAM were *Usefulness, Ease, Enjoy, Attitude and Intentions.* We added four latent variables representing social responses (*Beliefs, Compliance, Reactance and Liking*) in the PAAM.

Psychometric properties of the PAAM

Similar steps as in the earlier section were taken in running the confirmatory factor analysis.

<u>Average Variance Extracted (AVE)</u>

Almost all latent variables, except Liking, presented AVE higher than 0.50. To ensure convergent validity, two observed variables of Liking which have factorial loads less than 0.50 were removed from the analysis (confident and informed). As results, AVE for Liking increased to 0.48 but still, the construct did not converge with a satisfactory range. The elimination of two more Liking observed variables (interesting and competent) with the factorial loads less than 0.60 permitted AVE to increase to 0.54. All AVE showed satisfactory results, presenting in all latent variables higher than 0.50.

<u>Composite Reliability (CR)</u>

The consistency values of all latent variables (Cronbach's α) ranging from 0.74 to 0.94 were satisfactory (above 0.70 thresholds). Results showed CR values for the PAAM also ranged from 0.74 to 1.00, which is an indication that composite reliability was not an issue.

Discriminant Validity (DV)

By using Fornell-Larcker Criterion (Fornell & Larcker, 1981), it can be observed that the correlation of *Beliefs*' observed variables was higher for *Liking* than *Beliefs*. Thus, two observed variables for *Liking* (*interesting* and *honest*) that have smallest differences in factorial crossed loads were taken out from the analysis, thus confirming discriminant validity.

Collinearity Statistics (VIF)

The PAAM did not have any multicollinearity issue, with inner VIF ranges from 1.00 to 3.20.

Evaluation of the PAAM

Similar to the earlier model testing, the hypotheses for the PAAM were tested by examining the path coefficients and the significance level (t-test) of the model (Henseler & Sarstedt, 2013) using bootstrapping (Chin, 1998) with 1000 subsamples (recommended by Hair Jr et al. (2016)). Results demonstrated that *Compliance* has no effect in predicting *Attitude, Reactance* has no effect in predicting *Attitude*, and *Usefulness* has no effect in predicting *Intentions* (from original TAM) with f^2 smaller than 0.02. Other predictors have significant effects in predicting the respective predicted variables.

To design the final version of the PAAM for the acceptance of persuasive robots, the insignificant paths from the hypothesis testing were eliminated one-by-one, starting with the path that has no effect size. At the same time, the changes of *p* values for other paths were observed after each path elimination. The insignificant paths from the TAM (Davis et al., 1989; Venkatesh & Davis, 2000) (as shown in Figure 8.3) were retained in the final model to preserve the prediction by the original TAM (Davis et al., 1989; Venkatesh & Davis, 2000). As results, only two paths from the hypothesis for social responses prediction were removed: *Compliance* to predict *Attitude* (H1a), and *Reactance* to predict *Attitude* (H4). The rest of the paths were statistically significant.

Predictions based on TAM showed that *Usefulness* was a predictor for *Attitude* (f^2= 0.08) with small effect size but not a predictor for *Intentions* (f^2= 0.00). Whereas, with small effect, *Ease* was a predictor for *Usefulness* (f^2= 0.06), *Ease* was predicted by *Attitude* (f^2= 0.10) and *Enjoy* predicted *Ease* with medium effect (f^2= 0.27). Importantly, *Attitude* has a large effect in predicting *Intentions* (f^2= 0.75).

Hypothesis 1 was rejected. That is, *Attitude* (f^2= 0.00) and *Intentions* (f^2= 0.01) were not predicted by *Compliance*. *Reactance* (f^2= 0.09), *Usefulness* (f^2= 1.12), *Attitude* (f^2= 0.02) and *Compliance* (f^2= 0.19) were significantly determined by *Beliefs*, therefore Hypothesis 2 was accepted. Importantly, *Beliefs* have a large effect in predicting *Usefulness*, a medium effect in predicting *Compliance*, and a small effect in predicting *Reactance* and *Attitude*. Hypothesis 3 predicted that higher *Liking* causes higher *Beliefs* and *Intentions*, while causes lower *Reactance*. This hypothesis was confirmed by all significant paths, and *Liking* has a large effect on predicting *Beliefs* (f^2= 1.26) and a small effect on other predictions (f^2= 0.07 for *Intentions* and f^2= 0.03 for *Reactance*). Hypothesis 4 was rejected, in which *Reactance* was not a predictor for *Attitude* (f^2= 0.01). Hypothesis 5 was accepted with *Ease* predicting *Liking* with medium effect size (f^2= 0.15). Hypothesis 6 was accepted. That is, *Enjoy* was a predictor for *Liking* (f^2= 0.20), *Attitude* (f^2= 0.15) and *Intentions* (f^2= 0.03) with small effect size.

We also observed the path coefficient for each prediction in this analysis (refer to Figure 8.4). More importantly, the PAAM illustrates the increment of R^2 values for *Attitude* and *Intentions* compared to the earlier TAM (model without the social responses shown in Figure 8.3). That is, a large R^2 for *Attitude* (0.61) and a large R^2 for *Intentions* (0.76).

8.3.4 Objective 3

This study was also aimed to test whether the social responses add predictive power to the TAM specifically for the persuasive robot. Using the same method as in (Piçarra & Giger, 2018), we compared the R^2 for *Attitude* and *Intention* from TAM and PAAM (inclusion of social responses) by calculating the F-ratio and its significance.

In evaluating the goodness of fit for partial least square (PLS) method for SEM, Henseler and Sarstedt (2013) claimed that global goodness of fit for PLS proposed by Tenenhaus, Amato, and Esposito Vinzi (2004) did not represent a fit measure. Later on, Hair Jr et al (2016) highlighted that there was no global goodness of fit in PLS. Thus, in this study, we used R^2 (also known as the coefficient of determination) value as the model's predictive in judging the quality of the PAAM (Henseler & Sarstedt, 2013). The R^2 for each endogenous variable was evaluated since it reflects the fitness of the model in the context of regression analysis. If the model fit the data 100%, or in other words the model explains all of the variations in the endogenous variable, then the R^2 for such variable is equal to 1.00. The R^2 value was used in the earlier study (Pal, Triyason, Funilkul, & Chutimaskul, 2018) especially in human-robot interaction applications (Piçarra & Giger, 2018; You & Robert, 2018) as the model-fit measure (Bollen & Long, 1992). According to Cohen (1988), R^2 of 0.02, 0.13 and 0.26 are considered as small, medium and large effects respectively in the field of social and behavioural science.

As results, the R^2 for *Attitude* and *Intentions* increased with the inclusion of social responses based on the observation of overall prediction using SmartPLS. That is, 9.1% increment of R^2 for *Attitude* (TAM: 0.52 and PAAM: 0.61). Also, the inclusion of social responses in the PAAM (R^2 of 0.76) compares to the TAM (R^2 of 0.73) resulting in the increment of 2.8% explained the variance for *Intentions*. To examine the significances of the *R^2's* increments, we ran hierarchical multiple regression using SPSS since SmartPLS does not offer such a test. Hierarchical multiple regression analysis is a framework for model comparison rather than a statistical method. This analysis is effective in comparing multiple regression models by evaluating the changes of R^2 and its significance. It determines whether the increment (or decrement) of R^2 value for the dependent variable (e.g., *Attitude)* is statistically significant after including a new set of independent variables (we call it as model 2) into the original set of independent variables (we call it as model 1) (Ahmed, Qin, & Aduamoah, 2018; Teeroovengadum, Heeraman, & Jugurnath, 2017). This analysis was conducted in earlier research by extending TAM (Davis et al., 1989) with the evaluation of robot characteristics in predicting robot acceptance (Ezer, 2008) and extending TRA (Fishbein & Ajzen, 1975) with a key determinant from TPB (Ajzen, 1985) in determining the intention to work with a social robot (Giger & Piçarra, 2017).

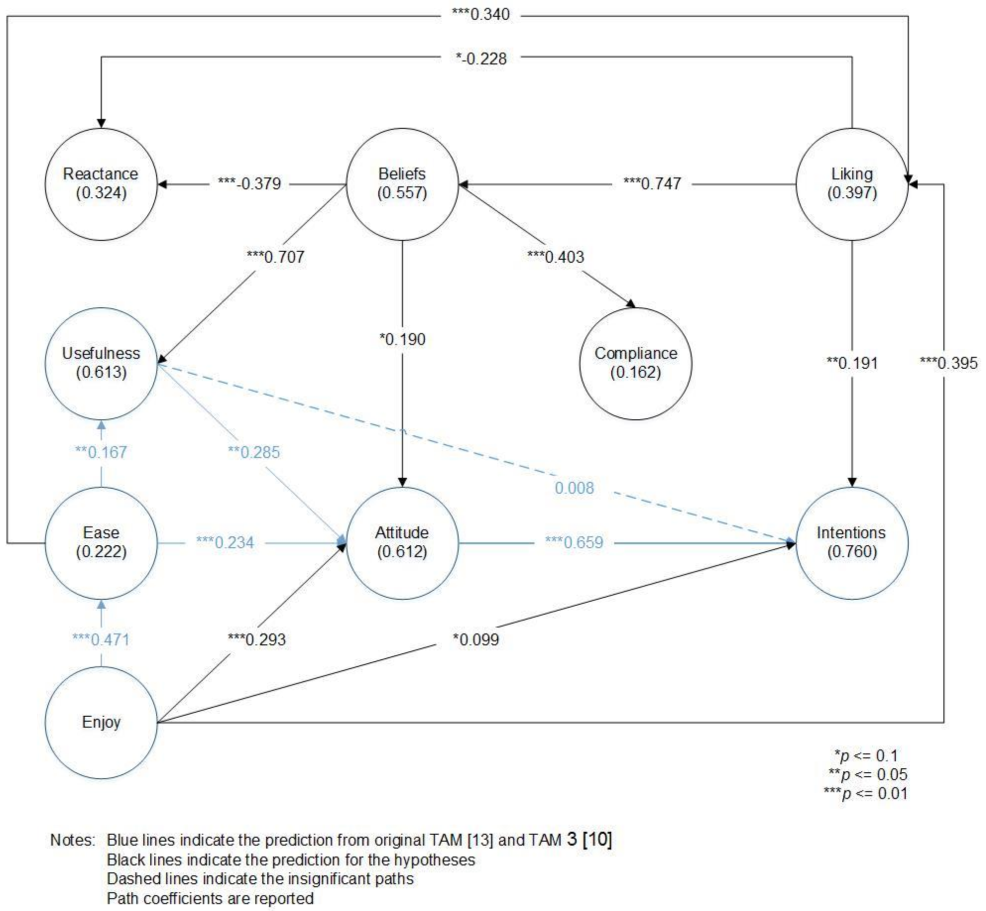


Figure 8.4: Final PAAM: integration of technology acceptance model (TAM) and social responses.

To compare the changes of *Attitude* from TAM and PAAM, we ran hierarchical multiple regression with *Attitude* as dependent variable, *Usefulness* and *Ease* as independent variables for the first model (based on TAM) besides *Beliefs* and *Enjoy* as additional independent variables for the second model (based on PAAM). Results demonstrated that the addition of *Beliefs* and *Enjoy* (model 2) led to a statistically significant increase in R^2 of 9.5%, $F(2, 73) = 8.02$, $p < 0.001$. The full model of *Usefulness*, *Ease*, *Beliefs* and *Enjoy* to predict *Attitude* was statistically significant, $R^2 = 0.58$, $F(4, 73) = 25.18$, $p < 0.001$.

We ran another hierarchical multiple regression to determine if the addition of *Enjoy* and *Liking* improved the prediction of *Intentions* (model 2) over and above *Attitude* and *Usefulness* alone (model 1). It turns out that the addition of *Enjoy* and *Liking* to the prediction of *Intentions* (model 2) led to a statistically significant increase in R^2 of 2.9%, $F(2, 73) = 4.20$, $p < 0.05$. The full model of *Enjoy*, *Liking*, *Attitude* and *Usefulness* to predict Intentions was statistically significant, $R^2 = 0.75$, $F(4, 73) = 54.81$, $p < 0.001$.

In summary, these hierarchical multiple regressions demonstrated clearly that including social responses: *Beliefs* in predicting *Attitude* and *Liking* in predicting *Intentions*, enhances the predictive power of the acceptance of persuasive robot as demonstrated by PAAM.

8.4 Discussion

This work enriches the body of research on TAM from the standpoint of social robotic user acceptance field. The first goal of the study was to empirically test the TAM in explaining the acceptance of persuasive robots. To achieve this goal, we employed five latent variables originated from original TAM (Davis et al., 1989) and TAM 3 (Venkatesh & Bala, 2008) namely perceived usefulness, perceived ease of use, perceived enjoyment, attitude towards using and behavioural intentions. Our results suggested that TAM demonstrates good predictive powers in understanding the acceptance of persuasive robots with satisfactory and high R^2 for attitude towards using and behavioural intentions (Heerink et al., 2010a) respectively. Earlier research showed comparable R^2 values for attitude towards using (R^2 = 0.61 (Park & Del Pobil, 2013)) and for behavioural intentions (R^2 = 0.63 (Heerink et al., 2009), R^2 = 0.53 (Park & Del Pobil, 2013)) in measuring the acceptance of social robots in separate studies. Other studies which used TAM in different domains such as in predicting consumers' intentions to purchase travel online (Amaro & Duarte, 2015) found satisfactory R^2 for attitude towards using and behavioural intentions (R^2=0.62, R^2=0.67) respectively. Among the constructs, perceived usefulness was the strongest predictor of attitude towards using (stronger than perceived ease of use) (Yu, Ha, Choi, & Rho, 2005) whereas attitude towards using was the only predictor of behavioural intentions. While some of the earlier works in social robotics found perceived usefulness to be a significant predictor of behavioural intentions (Conti et al., 2017; Heerink et al., 2010a), our results showed that perceived usefulness has no direct causal effect in predicting behavioural intentions. Further analysis reported that attitude towards using was a full mediator between perceived usefulness and behavioural intentions, similarly as expected in the original conceptualization of TAM (Venkatesh, 1999). This might be due to a large effect of attitude towards using on predicting behaviour intentions, which in return diminishes the power of perceived usefulness in predicting behaviour intentions. Mediation in TAM constructs were commonly found in earlier studies (Agarwal & Prasad, 1999; Burton-Jones & Hubona, 2006) (e.g., Burton-Jones and Hubona (2006) showed that beliefs about ease of use was a full mediator of the relationship between level of education and beliefs about usefulness). Applying to our study, the mediation analysis reflected that when people perceived the persuasive robot as a useful advisor in selecting the charity organizations, they would have a favourable attitude towards using the robot, which in turn influenced them to use the robot again in the future.

The evaluation of social responses towards the persuasive robot demonstrated a promising result for a better understanding the acceptance of persuasive robots. By extending the TAM constructs used in the first objective, we expected to increase the power of the acceptance model by adding social responses in the PAAM (second objective). The social responses include trusting behaviour, trusting beliefs, psychological reactance and liking. As expected, trusting beliefs and liking fitted in the PAAM by its contribution to the increment of R^2 for attitude towards using and behavioural intentions correspondingly. Earlier research pointed out the role of trust in enhancing user's acceptance and intention to use for technologies in general (Chauhan, 2015; Pavlou, 2003), and social robots in particular (de Boer & Åström, 2017; McMurray et al., 2017). Importantly, trusting beliefs was the strongest predictor of perceived usefulness. People who believe the robot will find it a useful advisor in selecting the best charity organizations for donation task. Additionally, Cialdini and Cialdini (2007) highlighted that liking is one of the weapons in the principle of persuasion. As a part of intrinsic motivation suggested by Cognitive Evaluation Theory (Deci & Ryan, 1985), liking can be increased by interacting with someone that pays us compliments and have some similarity to us (Cialdini, 2009). Since the persuasive robot in this study used social cues that people like (as identified in Part 2), it helps to increase the persuasive power of the robot in persuading people to experience less reactance towards the persuasive attempts. Indirectly, liking enhances predictive power in explaining the behavioural intentions to use the robot in case the participants have the access to the robotic advisor again.

On the other hand, compliance did not determine the attitude towards using or behavioural intentions in using the persuasive robot again in the future. This result is in line with earlier research (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000) which associated compliance to the management asking them to use a system with social influences, and which found no evidence that higher compliance led to higher attitude towards using the technology (Wu & Chen, 2017). This finding may be due to the task designed in this experiment. We asked the participants to donate the money to ambiguous charity organizations, which caused them to comply with the advice given by the robot although they have low favourable attitudes towards using the robot. Similar to compliance, psychological reactance also was not a predictor for attitude towards using the robot, even though psychological reactance was predicted by liking and trusting beliefs. The likeable social cues implemented on the persuasive robot could be the reason why the psychological reactance score is low. In this study, psychological reactance was skewed on the right side (positive skewness) with a very low mean value, M =1.02 (neutral = 3). It indicates that the persuasive attempts in this experiment did not trigger any significant feelings of anger and negative cognitions towards the robot.

One of the most important results from this study is the significant increment of R^2 (also known as the coefficient of determination) for attitude towards using and behavioural intentions constructs by the inclusion of social responses, particularly trusting beliefs and liking in the PAAM. By including perceived enjoyment and trusting beliefs as predictors of attitude towards using, the coefficient of determination for attitude towards using increase by 9.1% in the overall PAAM compared to the TAM. Whereas, the additional prediction by perceived enjoyment and liking increased the coefficient of determination for behavioural intentions by 2.8% in the overall PAAM compared to the TAM.

8.5 Summary

This chapter revealed that TAM demonstrates good predictive powers in understanding the acceptance of persuasive robots. Importantly, trusting beliefs and liking of the persuasive robots were reliable predictors of attitude towards using and behavioural intentions in our proposed Persuasive Agents Acceptance Model (PAAM) respectively. Our results also demonstrated that PAAM significantly has higher power in predicting the acceptance of persuasive robot compared to TAM.

In the last chapter, we present the general conclusions of the thesis by formulating our findings to the research questions. We also discuss the design implications in developing social cues for persuasive robots, the limitations of our studies, the suggestions for future research and the ethical issues related to persuasive attempts using persuasive robots.

CHAPTER 9

General Conclusion

In this chapter, we summarize the work presented in the earlier chapters by responding to the research questions posed in Chapter 1 (Introduction). Then, we detail the design implications learnt from the studies conducted and reflect on ethical considerations in designing persuasive robots. We end this chapter by addressing the limitations of our current studies and providing recommendations for future work.

9.1 Research Conclusion

Recent research (Hammer, Lugrin, Bogomolov, Janowski, & André, 2016; Lee & Liang, 2016; Lee & Liang, 2018; Sumi & Nagata, 2013) suggested that social robots have promising roles to play in persuasion. However, earlier research has barely touched upon the influence of social cues displayed by persuasive robots on human responses. To address this issue, we investigated the influence of the number of social cues (none vs. minimal vs. enhanced social cues in **Part 1** of the thesis) and the characteristics of social cues (non-interactive and interactive social cues in **Part 2** of the thesis) upon the users social responses (psychological reactance, compliance, trusting beliefs and liking). Finally, we investigated the roles of social responses in predicting the acceptance of persuasive robots in **Part 3** of the thesis. To conclude, we address each of the research questions formulated in **Chapter 1** separately.

In **Part 1** we aimed to test Social Agency theory (Mayer et al., 2003). That is, we investigated whether an agent that has stronger (or more) social cues is also more persuasive than an agent that has weaker (or less) social cues. As argued previously in Chapter 1, we conducted a preliminary study (see **Chapter 2**) to examine more closely the human perception of social agency of a robot based on displaying individual cues, pairs or combinations of three social cues: emotional intonation of the robot's voice, the robot's head movement and its facial expressions. We assessed the user's perception of the robot's social agency by asking the participants to evaluate the resemblance of the robot (with its social cues) to the representations of a real person and living creature likeness. Thereby, we could study the following research question.

> **Research Question 1.1:**
> *Which social cues should a robot have so that people perceive the robot as the most representing a real person and the highest likeness to a living creature?*

As suggested by the Theoretical Model of Social Influences (Blascovich, 2002b), in this study we found that the more social cues one added to the SociBot, the more people perceived the robot as resembling a real person and the highest the likeness they reported it to have to a living creature. Thus, a robot combining all three social cues (emotional intonation voice, facial expression and head movement) was found to have the closest to the representation of a real person and the most living creature likeness. Based on these findings, in Part 1 of the thesis we equated the social agency with the richness of social cues by claiming that the higher number of social cues implemented on the robots, the higher the social agency of the robots.

Returning to the aim of **Part 1**, based on Social Agency theory (Mayer et al., 2003) the question was raised whether persuasive attempts by persuasive robots with stronger (or more) social cues will be more effective (leading to higher compliance) and will be perceived more positively (leading to lower psychological reactance) than persuasive attempts by persuasive robots with lower social agency. To investigate this issue, a series of studies were carried out (see **Chapter 3**, **Chapter 4**, and **Chapter 5**) where we presented participants with persuasive social agents that had different levels of social agency: an advisory text (low social agency), a robot with minimal social cues; neutral face and blinking eye (medium social agency), and a robot with enhanced social cues (emotional intonation voice, head movement and facial expression (high social agency). Thereby, we could study the following research question.

Research Question 1.2:
What is the influence of the number of social cues used by persuasive robots on psychological reactance and compliance responses?

To manipulate the level of persuasiveness of the robot, next to the number of social cues, we also manipulated the coerciveness of the language used by the persuasive agents: slightly (pleasant) vs. highly (forceful) coercive language in **Chapter 3,** thereby to trigger psychological reactance.

Research Question 1.2 (a):
What is the influence of the number of social cues and the coerciveness of the language used by persuasive robots on psychological reactance and compliance responses?

The study described in **Chapter 3** revealed that a) the number of social cues and the of coerciveness of language were found to have no effect upon psychological reactance b) a higher coerciveness of language led to higher compliance, independently of the number of social cues displayed by persuasive robot. Based on these findings, we concluded that language coerciveness is a predominant factor in determining the compliance response towards persuasive attempts. That is, people comply more with the persuasive robots that use highly coercive (forceful) language compared to the robot with slightly coercive (pleasant) language. Despite the coerciveness of the language, this study did not find any influence of the number of social cues upon the level of psychological reactance and the compliance. We argued that it might be due to the low levels of participant's involvement in the game-task used in **Chapter 3**. Specifically, participants in this study were asked to decide on the ingredients for a drink for an alien – one could reasonably expect that they did not care much about the outcome of the task. Because of this low involvement in the task it would be relatively easy for a persuasive attempt to be effective, independent of the number of social cues.

To counter this involvement issue and to provide evidence for Social Agency theory (Mayer et al., 2003), we designed a study in **Chapter 4** that uses the same manipulation of the number of social cues as in **Chapter 3**, while adding a manipulation of psychological involvement to the study: low involvement (creating alien's drink) vs. high involvement (creating a drink for yourself) in this study.

Research Question 1.2 (b):
What is the influence of the number of social cues and the psychological involvement used by persuasive robots on psychological reactance and compliance responses?

The experiment conducted in **Chapter 4** found that a) a higher number of social cues used by a persuasive robot and higher task involvement would lead to higher reactance, and b) higher task involvement would lead to lower compliance, especially when the appointed advisor was a robot with emotional intonation in spoken output, head movement and facial expression (high social agency condition). Based on the social responses shown, we concluded that a robot with enhanced social cues was perceived more like a real human by the participants during the persuasive attempts. This effect was stronger when the user felt involved in the task at hand (high psychological involvement). That is, we found that people experienced the highest psychological reactance and the lowest compliance toward persuasive attempts by an agent with the most social cues in the high psychological involvement task. In line with Social Agency theory (Mayer et al., 2003), this work suggests that a social robot presenting stronger (or more) social cues caused more social responses (psychological reactance and compliance) especially when people care about the task.

Overall, Part 1 aimed to find whether adding social cues to persuasive robots helps reduce psychological reactance and increase compliance during persuasive attempts by these robots. As results, **Chapter 5** revealed that a robot with minimal social cues (neutral face and blinking eye) invoked the lowest psychological reactance as compared to the robot with enhanced social cues (emotional intonation voice, head movement and facial expression) and advisory-text advisors. This finding is in agreement with earlier studies which reported that a robot with minimal social cues can elicit positive social responses such as increment of participants' performance in a game of guessing (Mutlu et al., 2009) and encouragement of interaction between children with autism and co-present adults (Robins et al., 2009). That is, robots with minimal social cues caused people (who were only involved in the task to a limit extent) to experience lower reactance (especially less negative cognitions) than the robots with enhanced social cues after being exposed to highly coercive language. In line with the Media Equation hypothesis (Reeves & Nass, 1996), this finding shows that simple social cues are sufficient to trigger social responses. To conclude **Part 1** of the thesis, the current research suggests that persuasive robots with minimal social cues (neutral face and blinking eyes) with highly (forceful) coercive language should be used as persuaders so that persuasive attempts will be positively perceived (causing little psychological reactance) by human user.

In **Part 2**, we aimed to test which social cues implemented into an artificial social robot make it more persuasive. As suggested by the Social Agency theory (Mayer et al., 2003) and the Social Cues hypothesis (Louwerse et al., 2005), we argued that humans exhibit more social responses to persuasive robots with human-like features than to persuasive robots with less human-like features. However, this theory and this hypothesis leave a question open: *which* human-like features will be effective and perceived positively by humans in persuasive attempts by robots. Therefore in **Part 2**, we investigated the influence of specific human-like features of social cues. That is, we studied the influence of two types of human-like features on the user's social responses: non-interactive social cues, which are social cues that are not dependent on user responses (in **Chapter 6**) and interactive social cues, which are social cues that are dependent on user responses (in **Chapter 7**).

In the study described in **Chapter 6**, we manipulated two types of *non-interactive* social cues of a persuasive robot. These non-interactive social cues were selected based on earlier studies (Oosterhof & Todorov, 2009; Todorov et al., 2015; Todorov & Oosterhof, 2011) (Pfeifer & Lugrin, 2018; Sandygulova & O'Hare, 2018; Siegel et al., 2009; Tay et al., 2014) which provide feasible and suitable manipulation of social cues that fit our overarching research question for the thesis. More specifically, we presented the participants with persuasive robots that had different facial characteristics. Earlier studies (Oosterhof & Todorov, 2009; Todorov et al., 2015; Todorov & Oosterhof, 2011) found that 2D images of a man with specific facial characteristics influence the evaluation of trust towards interaction partner. Nevertheless, these results are still equivocal in the context of this thesis because those facial characteristics have not yet been tested in a robot. Building on the earlier work (Oosterhof & Todorov, 2009; Todorov et al., 2015; Todorov & Oosterhof, 2011), we implemented our robot a face with more trustworthy facial characteristics or a face with less trustworthy characteristics (upturned or downturned eyebrows and lips). Another non-interactive social cue that we manipulated was the gender of the robot (thereby manipulating gender similarity). We selected gender as the second manipulation in this study since it is easy to manipulate and the available literature is inconclusive as to which gender a robot should appear to have in order to be more persuasive (Crowelly et al., 2009; Eyssel & Hegel, 2012; Eyssel et al., 2012; Powers et al., 2005; Siegel et al., 2009). Other than psychological reactance and compliance, we also added trusting beliefs as an added social response measures in this study. Thereby, we could study the following research question.

> **Research Question 2.1:**
> *What is the influence of facial characteristics and gender similarity used by persuasive robots on psychological reactance, compliance and trusting beliefs responses?*

The findings in **Chapter 6** regarding *non-interactive* social cues of persuasive robots showed that people experienced a) lower psychological reactance when the robot featured the most trustworthy face and had a gender similar to the user, b) stronger trusting beliefs toward a robot with the most trustworthy face, independent of the robot's gender, c) higher compliance towards a robot with most trustworthy face, independent of the robot's gender, and d) higher compliance towards a female robot than towards a male robot. We also found that e) psychological reactance was negatively correlated with trusting beliefs, and e) liking is a full mediator between facial characteristics and social responses (psychological reactance and trusting beliefs). Based on these findings, we concluded that persuasion activity could be more effective (high compliance), and cause less psychological reactance and stronger trusting beliefs by designing facial characteristics of robots to match those known from social psychological research to evoke trust in people (most trustworthy face). That is, the persuasive robots should have upturned eyebrows and lips as its facial characteristics. In line with the Similarity-Attraction hypothesis (Byrne, 1971), we also found that personalizing persuasive robots to match the gender of the users could also cause less psychological reactance.

In addition to the *non-interactive* social cues, we also investigated the effect of human-like *interactive* social cues on social responses (in **Chapter 7**). More specifically, we presented participants with a persuasive robot that displayed either random head movements and random social praise (in the no interactive social cues condition), or a persuasive robot that displayed head mimicry only without social praise (in low number of interactive social cues condition), or head mimicry and properly timed social praise (in high number of interactive social cues condition). Apart from psychological reactance, compliance and trusting beliefs, we also assessed the extent to which the participants liked to interact with the robot with such cues. Thereby, we could study the following research question.

> **Research Question 2.2:**
> *What is the influence of head mimicry and social praise used by persuasive robots on psychological reactance, compliance, trusting beliefs and liking responses?*

The study described in **Chapter 7** suggested that a) head mimicry and proper timing for praise invoked less psychological reactance and more liking towards persuasive robots, and b) social praise enhanced trusting beliefs toward persuasive robots, independent of the timing of that social praise. Based on these findings, we concluded that *interactive* social cues such as head mimicry and properly timed social praise encourage positive responses (especially less psychological reactance and more liking) toward persuasive attempts. Furthermore, this study suggested that c) the more a participant liked the persuasive robot, the less a participant showed reactance towards that persuasive robot, and d) the more a participant liked the persuasive robot the more the participant believed the robot is trustworthy.

Overall, Part 2 aimed to find which social cues should be implemented in persuasive robots to attain low psychological reactance, high compliance, high trusting beliefs and high liking during persuasive attempts by robots. Human-like features were implemented as social cues in order to triggers positive social responses in line with the Social Agency theory (Mayer et al., 2003), the Theory of Anthropomorphism (Epley et al., 2007) and the Social Cues hypothesis (Louwerse et al., 2005). The two studies described in **Chapter 6** and **Chapter 7** revealed that robots with similar gender with the users significantly contribute to low psychological reactance, while robots with the most trustworthy facial characteristics, head mimicry and interactive social praise significantly contribute to high trusting beliefs and low psychological reactance. As in Chapter 6 (similarity of gender), the study in Chapter 7 also showed that humans like more those robots that mimic them (in our case similarity of head's movement) as suggested by Similarity-Attraction hypothesis (Byrne, 1971).

After having investigated how to design social cues for persuasive robots in **Part 1** and **Part 2**, **Part 3** of this thesis addressed the roles of social responses (psychological reactance, compliance, trusting beliefs and liking) for predicting the acceptance of persuasive robots. As social responses that might contribute to the acceptance of persuasive robots, we used all positively perceived social cues presented in Chapter 2 until Chapter 7. In this final study (see Chapter 8), we investigated whether social responses (psychological reactance, compliance, trusting beliefs and liking) are amongst the key determinants for the acceptance of persuasive robots. More specifically, we implemented minimal (neutral face and blinking eye) and likeable (most trustworthy face: upturned eyebrows and lips, head mimicry, proper timing for social praises) social cues into persuasive robots in this study to answer the following research question.

> **Research Question 3:**
> *Do social responses add predictive power to the technology acceptance model of persuasive robots?*

The research findings in **Chapter 8** showed that a) the Technology Acceptance Model (known as TAM) (Davis et al., 1989; Venkatesh & Bala, 2008) can explain the acceptance of persuasive robots b) integrating social responses within TAM (Davis et al., 1989; Venkatesh & Bala, 2008) significantly increased the prediction power of persuasive robots acceptance. Specifically, our findings revealed that trusting beliefs and liking (the social responses) significantly added predictive power regarding the acceptance of persuasive robots. However, no contribution of psychological reactance and compliance were found in the proposed model, probably due to insufficient variation of psychological reactance and ambiguous task selections.

Finally, we put together all the points from earlier studies (c.f. **Chapter 3** until **Chapter 8**) to answer this overarching research question:

> **Overarching Research Question:**
> *How to design social cues for persuasive robots so that the persuasive attempts will be effective, and positively perceived by humans?*

We conclude this thesis by providing evidence that persuasive robots should have the following social cues to make the persuasion activities more effective (high compliance and high acceptance), and positively perceived by humans (low psychological reactance, high trusting beliefs and high liking):

1. Minimal (neutral face with blinking eye), and likeable (upturned eyebrows and lips, head mimicry and proper timing for social praises) social cues
2. Gender similar to the users
3. Use highly coercive (forceful) language
4. Persuasion in general (low involvement) issue only

9.2 Design Implications

Prior research has shown that social cues allow people to experience interactions with social robots in both positive and negative ways. The connection between social cues of the robots and social responses by humans is conceptually intriguing because both of them are important elements in the persuasion activity especially when we design robots to be used as persuasive agents. Hence, this thesis contributes to understanding the limitations of the earlier designs of persuasive robots.

This thesis aims to fill in a gap in the research field of persuasive technology especially with regards to the design of persuasive robots; it enriches the literature in the area of social responses towards persuasive attempts by robots, and focuses on the roles of social responses in the acceptance of persuasive robots. More specifically, the studies reported in Chapter 2 to Chapter 7 highlighted the influence of social cues on human social responses in persuasive attempts. Later on, we emphasized the contribution of social responses in the acceptance model of persuasive robots in Chapter 8.

By focusing on the characteristics of social cues in the Part 1 of the thesis, we learnt that persuasive robots should be designed only with neutral face and blinking eyes as social cues (and not adding emotional intonation voice, head movement and facial expression) to decrease the level of psychological reactance. As highlighted by the philosophical principle related to ontological simplicity known as Occam's razor (Feuer, 1957), our findings show that social cues for persuasive robots should not be multiplied unnecessary. These findings are in line with earlier studies (Beira et al., 2006; Raptis, Jensen, Kjeldskov, & Skov, 2017; Sosa, Montiel, Sandoval, & Mohan, 2018; Trier & Richter, 2013) which highlighted the importance of simplicity in design, as complexity may bring negative impact on users in terms of low effectiveness of design and demolished trust (Karvonen, 2000; Nadkarni & Gupta, 2007) in several domains such as in human-computer interaction. From a study in Chapter 2, we also learnt that people perceived a robot with the most social cues (emotional intonation voice, head movement and facial expression) as having the closest representation of a real person and living creature likeness as suggested by Theoretical Model of Social Influences (Blascovich, 2002b) compared to the robot with less social cues. Using those social cues as the highest social agency condition in the next studies, we learnt from the experiment described in Chapter 3 that using a highly coercive language for persuasive agents (independent of the social agency) can enhance the chances of compliance. Whereas in Chapter 4, we learnt that the level of involvement towards the issue at hand controls the level of psychological reactance and compliance. That is, people experienced high psychological reactance and low compliance when being persuaded by robots that have the highest social agency in high involvement tasks.

By focusing on the characteristics of social cues in the Part 2 of the thesis, we learnt that liking is a mediator for trusting beliefs and psychological reactance. Hence, it is essential for human-robot interaction designers to model likeable social cues such as most trustworthy facial characteristics, head mimicry and social praises for social robots to elicit positive social responses (especially high trusting beliefs and low psychological reactance) from the users as shown in Chapter 6 and Chapter 7. Adding to the Pleasure-Interest Model of Aesthetic Liking (Graf & Landwehr, 2015), our results showed that pleasure-based liking and interest-based liking toward design not only increase liking, but also increase trusting beliefs and decrease reactance in human-robot interaction. Additionally, we learnt from Chapter 6 that persuasiveness of social robots can also be enhanced using a female robot. However, a drawback of using a female robot as a persuader is that it may cause higher psychological reactance to participants compared to a male robot. Based on the gender of the persuasive robots, we also can conclude that persuasiveness of such an agent (in terms of compliance) and psychological reactance are not related.

Part 3 of the thesis showed that it is essential to design social cues that people like and believe to be trustworthy in order to enhance the acceptance of persuasive robots. As suggested by

Principle of Robotics (Boden et al., 2017), robots should be designed and operated from the beginning in a way that they can occupy people's trust and confidence to be used in daily life by complying with existing law (Asimov, 1942).

Figure 9.1 summarizes research findings on the design of social cues and its influence on social responses towards SociBot as a persuasive robot.

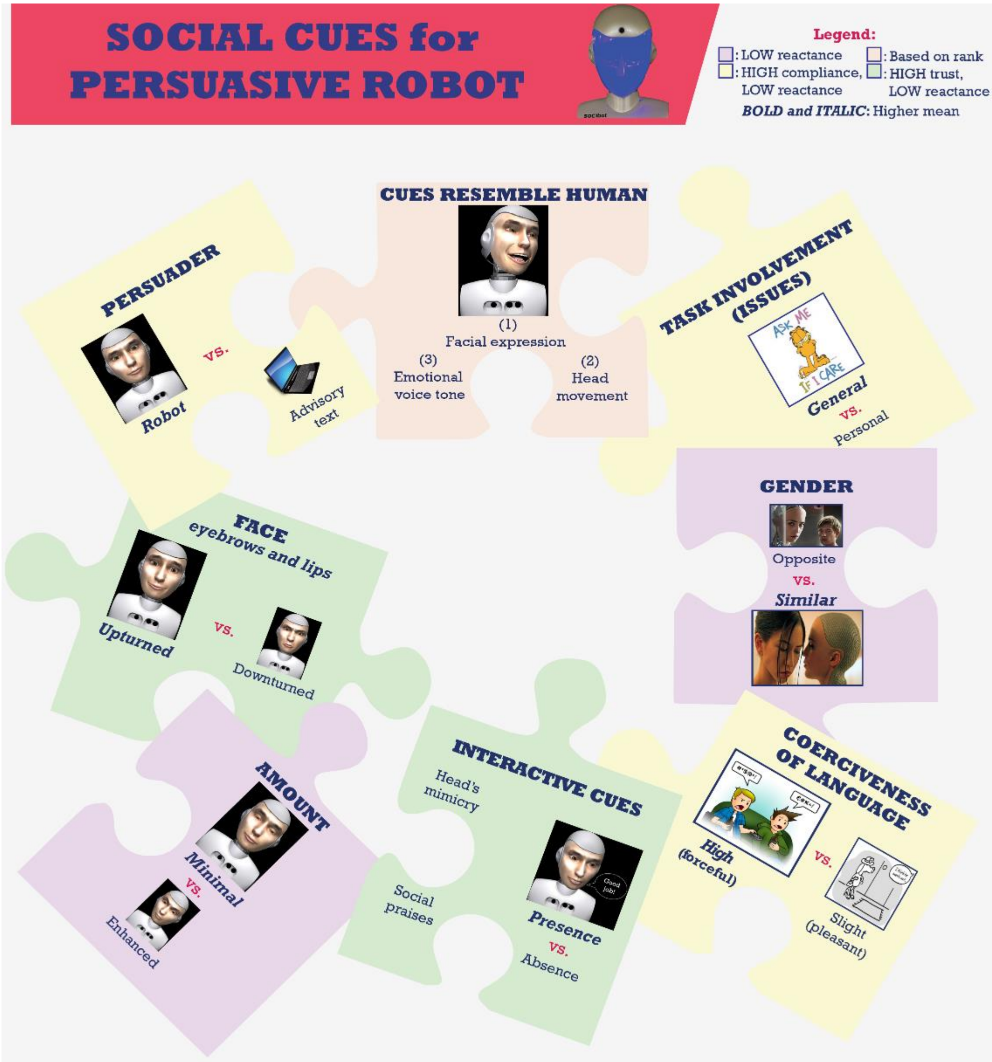


Figure 9.1: Proposed social cues for persuasive robots.

9.3 Limitations and Future Work

The experimental designs used have various limitations that can be addressed in future studies.

Interaction Setting

The scope of this work is restricted to well-controlled laboratory experiments. The venue and time for the experiment, allocation of the participants to the independent variable group, and standardized procedure were set by the experimenter prior to the actual experimental days. Future research could extend the work by investigating the influence of social cues on social responses using other research methods such as field experiments in a real-life setting. This can help to validate the findings presented in this study and can also ensure their robustness.

It is noteworthy that in current experimental settings, only one person participated in each experimental slot. As such, the findings in this study is limited to one-to-one persuasion. In the future, we hope to deploy an experiment for a group of people as persuadees to study the effect of social influence on social responses in different persuasion context.

Duration of Interaction

A longer duration of the interaction between the persuasive robot and humans may reveal changes in the nature of social responses over time. For our study, the participants took approximately fifteen to thirty minutes to finish the decision-making game, and the interaction between the persuasive robot and the participants lasted for a relatively short time. In the future, this experimental set up can be enhanced by ensuring a more sustained interaction between humans and the robot. This should be done to ensure that the social agency of the robot is sufficiently experienced, especially in long-term persuasion activities to change people's attitude and behaviours.

Objective Measures

Only a few social responses could be examined in these experiments: psychological reactance, compliance, trusting beliefs and liking. Despite these promising results, questions remain about how humans perceived persuasive attempts in terms of other social responses like engagement, and physiological response like heart rate variability (HRV). Additionally, the evaluation of other measures shall be added to enrich the understanding of using a robot as a persuader. Future research also could explore some strategies for enhancing the likeability of robots as a means to enhance persuasion and trust, and to delve more into the discrepancy between trusting beliefs and behaviours, and how these influence human-robot interaction in different application contexts.

We envisage other social cues, e.g. proximity between the users and the robot, as well as directing gestures could also impact social responses in ways that we do not yet know. For further research, we recommend to integrate these social cues with those social cues which have been found to be positively perceived by humans in the reported studies. Extending this work can help develop guidelines for the design of persuasive robots. Other than that, in Chapter 6 we found that female advisors caused higher psychological reactance than male advisors. It could be that the female advisor was less trustworthy than the male advisor based on the correlation analysis between psychological reactance and trusting beliefs. Thus, there could be a mono method bias here. To know if this is so, future research could test with more faces to reliably check if there is a main effect of robot gender. Further research may also consider enhancing PAAM by including other social responses like engagement and social attraction.

An earlier study (Appel, von der Pütten, Krämer, & Gratch, 2012) distinguished the impact of agency (high: avatar vs low: agent) and social cues (high: virtual human vs low: text chat) on social responses as two independent measures. Their results showed that the more social cues, the more sense of mutual awareness, positive characters and attention were paid by participants. They also found that the higher the agency, the higher the feeling of social presence was reported. On the one hand, the Theoretical Model of Social Influences (Blascovich, 2002b) defines social agency as the extent in which people perceive an agent as the representation of a real person in real time. On the other hand, in Chapter 2, we found that people perceived a robot with the most social cues as having the closest representation of a real person. Thus, we envision that the more social cues displayed by an artificial social agent, the higher the representation of that agent to a real person resulting the higher social agency of that agent. There is abundant room for further investigation of the interrelation between social cues and social agency using other humanoid robots.

Task Designed

In most of our experimental studies we did not find a significant effect of social cues on compliance. We are aware that this might be due to the task designed that limits the chances of successful persuasive attempts. For instance, by manipulating the gender of the robot in Chapter 6, we asked participants to create a drink for an alien without considering the possibilities of gender stereotyping of tasks as highlighted in earlier studies (Jeanquart-Barone & Sekaran, 1994; Tay et al., 2014). Thus, we suggest that future research could extend the current work by investigating the importance of robot gender (and similarity of robot gender with participant gender) when the robot's task is gender-stereotyped. Since we also did not find a significant effect of interactive social cues on compliance in Chapter 7, future research might explore the effect of social cues on compliance by using non-dichotomous activities such as offering more than one alternative options to the participants and increasing the number of tasks and thus also the number of persuasive attempts in such experiments.

9.4 Ethical Issues and Considerations

The laws of robotics also known as Asimov's Laws (Asimov, 1942) have being used as a baseline for ethical considerations in human-robot interactions. The laws stated that:

1. *A robot may not injure a human being or, through inaction, allow a human being to come to harm*
2. *A robot must obey any orders given to it by human beings, except where such orders would conflict with the First Law*
3. *A robot must protect its own existence as long as such protection does not conflict with the First or Second Law*

As emphasized in Asimov's Laws, ethical considerations are critical, especially when conducting a research project involving human subjects. Earlier research (Cavallo, Dario, & Fortunati, 2018; Duffy, 2006; Lin, Abney, & Bekey, 2014) highlighted several ethical issues concerning the use of technology such as social robots as interaction partners. These include the rules of etiquette such as greetings from the robots before starting and after finishing the experiment (Reeves & Nass, 1996) and the ethical code in designing social agents such as persuasive robots to preserve human autonomy, beneficence and non-maleficence (Anderson & Anderson, 2008). Earlier studies (Miller & Parasuraman, 2007; Riek, Rabinowitch, Chakrabarti, & Robinson, 2009) also raised the 'Turing Deceptions' issue in utilizing Wizard of Oz technique to control the robots in which may violate the social relationship between humans and robots. Riek and Howard (2014) argued that Wizard of Oz technique should be employed sparingly since the robots are used as a mediator or a social mask for programmers to 'hide' behind them and it may create confusion to the humans in determining the levels of robots' autonomy.

These ethical considerations are relevant to us as well since we used a persuasive robot in our studies. The ethics of persuasion in changing attitude or behaviour stress that the persuasion activities should be done to win people over, not to defeat them (Shell & Moussa, 2007). In line with ethical code elaborated previously (Anderson & Anderson, 2008), persuasion should respect human autonomy in making decisions. That is, free-will action and thinking need to be practiced in order to decide whether to follow or to ignore persuasive attempts. Hence, coercive techniques like using force to change others mind must be avoided (Berdichevsky & Neuenschwander, 1999).

Obviously, designing social cues for social robotics while considering social responses can be beneficial to humans. As pointed out by Ham and Spahn (2015), the problem of intentionality using social cues in robots to elicit social phenomena in human-robot interaction might raise several ethical issues. For example, implementing likable social cues such as head mimicry (c.f. Part 2 of the thesis) can reduce psychological reactance and increase trusting beliefs on persuasive robots unconsciously (Langer, 1992). However, persuasive robots with such social cues can be misused to persuade people to do bad things or to have negative thoughts on something. The question arises, who should be blamed when these things happen? It then becomes a complicated issue to deal with (Berdichevsky & Neuenschwander, 1999). As a solution, the Principles of Robotics (Boden et al., 2017) highlighted that it should be possible to find out who is responsible for each robot.

Moreover, some researchers (Shneiderman, 2010; Shneiderman & Maes, 1997) claimed that designing social cues for persuasive technologies (in our case persuasive robots) is unhealthy and unethical since it can mislead users about the true nature of the robots. However, Fogg (2002) defeated this argument by emphasizing that persuasive technologies can be designed to enhance humans' life such as promoting better lifestyle and supporting educational technologies so that they are more likely to indulge, accept, and perhaps embrace the persuasive social actors. Additionally, if all robots especially persuasive robots were designed by following the Principles of Robotics (Boden et al., 2017), this ethical issue should not be raised since robots are products. So, they should be designed to be safe, secure and not be used to exploit vulnerable users as with other products' rules.

9.5 Final Remarks

How to design social cues for persuasive robots so that the persuasive attempts will be effective, and positively perceived by humans?

Now we have a clear picture how Geppetto should design social cues for Pinocchio. For persuasion purposes, Pinocchio (in our case persuasive robots) should be designed with minimal (neutral face with blinking eye) and likeable (upturned eyebrows and lips, head mimicry and proper timing for social praises) social cues, have the same gender as you, will be better able to persuade you about general issues only for which you do not hold strong opinions (low involvement) and can use forceful (highly coercive) language when advising you about things that are for your own good such as waking up at 7 o'clock sharp to go to work, telling to you to eat healthy food at lunch, and reminding you to take your medicine before going to bed.

Thereby, persuasive robots can have a higher chance of helping people to attain behaviour change goals (perhaps for a better lifestyle) and enjoy higher acceptance by people.

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List of Publications

Journal publications

1. Effects of robot facial characteristics and gender in persuasive human-robot interaction (2018). *Frontiers in Robotics and AI*, *5*(73). DOI: 10.3389/frobt.2018.00073
2. The influence of social cues in persuasive social robots on psychological reactance and compliance (2018). *Computers in Human Behavior*, 87, 58-65. DOI: 10.1016/j.chb.2018.05.016
3. Assessing the effect of persuasive robots interactive social cues on users' psychological reactance, liking, trusting beliefs and compliance (2019). *Advanced Robotics*, 1-13. DOI: 10.1080/01691864.2019.1589570
4. Persuasive Robots Acceptance Model (PRAM): Roles of Social Responses within the Acceptance Model of Persuasive Robots (under review). *International Journal of Social Robotics*

Conference publications

1. Pardon the rude robot: Social cues diminish reactance to high controlling language (2017, August). Paper presented at *26th IEEE International Symposium on Robot and Human Interactive Communication* (pp. 411-417). IEEE. DOI: 10.1109/ROMAN.2017.8172335
2. The Influence of Social Cues and Controlling Language on Agent's Expertise, Sociability, and Trustworthiness (2017, March). In *Proceedings of the Companion of the 2017ACM/IEEE International Conference on Human-Robot Interaction* (pp. 125-126). ACM. DOI: 10.1145/3029798.3038410
3. Poker face influence: Persuasive robots with minimal social cues triggers less psychological reactance (2018, August). Paper presented at *27th IEEE International Symposium on Robot and Human Interactive Communication* (pp. 940-946). IEEE. DOI: 10.1109/ROMAN.2018.8525535
4. Investigating the Effect of Social Cues on Social Agency Judgement (in press). In *Proceedings of the Companion of the 2019ACM/IEEE International Conference on Human-Robot Interaction*. ACM.

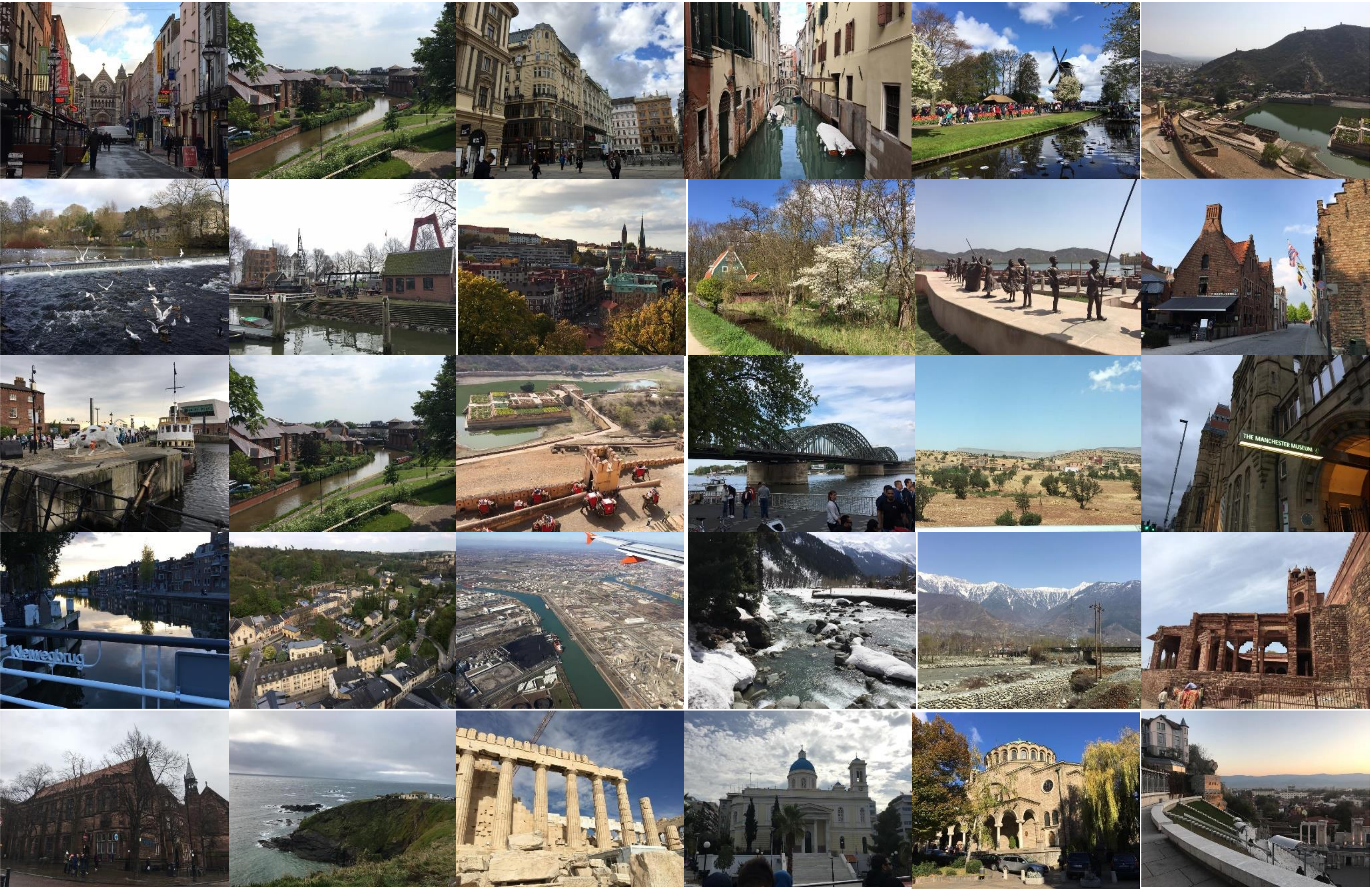
Biography

Aimi Shazwani binti Ghazali was born on 13-01-1988 in Pahang, Malaysia. In 2011, she received her first class Bachelor degree in Engineering (Mechatronics) (Honors) from International Islamic University Malaysia (IIUM). Later in 2015, she received her MSc. Degree in Mechatronics Engineering from same university.

From 2007, Aimi has involved in multiple research projects and have been recognized for its academic contributions. With her final year degree project entitled 'Design of Identification System for Early Warning of Vector Borne-Disease: Case Study of Aedes Mosquito', IIUM and its industrial partners awarded Aimi's bachelor thesis as the Best Poster Award in the Final Year Project Exhibition and a Silver Medal in IIUM Research, Invention & Innovation Exhibition (IRIEE) 2011. During her bachelor degree convocation in 2011, IIUM awarded Aimi as the Best Student (Academic) for Bachelor of Engineering (Mechatronics), Best Student in Robotics and Automation, Wahyudi Martono Award in Control and Instrumentation, and Rector's List sponsored by Shell Malaysia. In 2012, Aimi started her master degree with a dissertation entitled 'Development of in-the-loop Emotion Recognition System for Human Machine Interaction (HMI)' specifically for upper extremity rehabilitation platform. During her master degree, she has been awarded a Bronze Medal in British Invention Show (BIS) 2014, a Bronze Medal in IRIIE 2014, a Silver Medal in Persidangan Dan Eskpo Ciptaan Institusi Pengajian Tinggi Antarabangsa (PECIPTA) 2013 and a Silver Medal in IRIIE 2013.

Aimi worked as a tutor at Faculty of Mechatronics, IIUM for over two semesters during her final year of bachelor study. After graduation in 2011, Aimi worked as a graduate trainee (package designer) at Intel Microelectronics (M) Sdn. Bhd. for one year. Following her MSc degree, Aimi worked as a research assistant for her master project with a grant funding from Malaysia Ministry of Higher Education for two years. From December 2015, Aimi commenced a PhD project at Eindhoven University of Technology (TU/e), Eindhoven, the Netherlands of which the findings are presented in this dissertation. During her PhD, Aimi presented her works at several top-ranking conferences and journals related to human-robot interaction.

Currently, Aimi works as an academic trainee at IIUM. Her current research interests focus on developing biomechatronics systems and designing social robots for persuasion activities. Her future goal is to aid academic community in developing social robots for a better lifestyle.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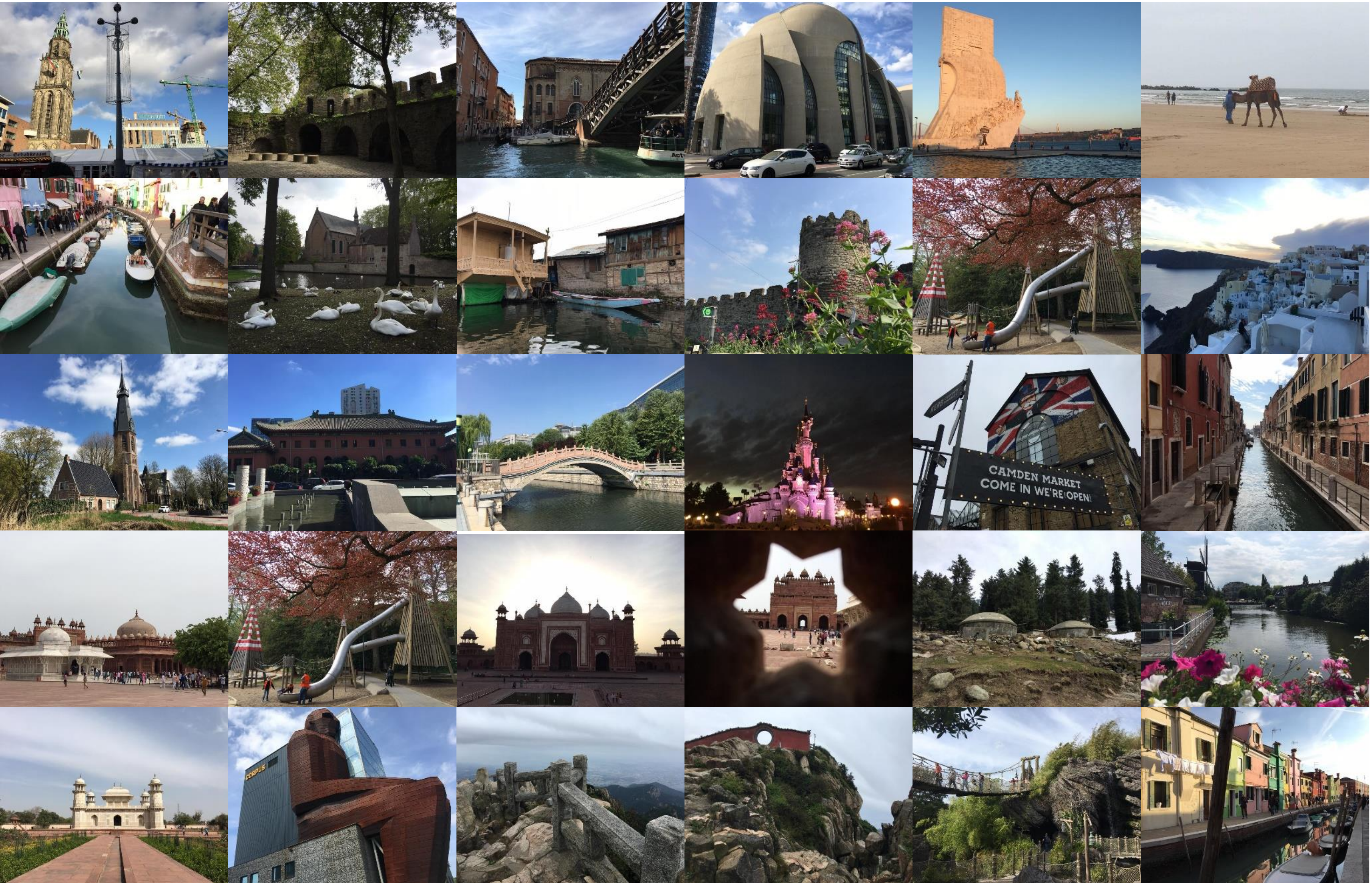
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It is impossible to persuade a man who does not disagree, but smiles.
-Muriel Spark

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