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Social Robots as Communication Partners to Support Emotional Well-Being

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Abstract

Interpersonal communication behaviors play a significant role in maintaining emotional well-being. Self-disclosure is one such behavior that can have a meaningful impact on our emotional state. When we engage in self-disclosure, we can receive and provide support, improve our mood, and regulate our emotions. It also creates a comfortable space to share our feelings and emotions, which can have a positive impact on our overall mental and physical health. Social robots are gradually being introduced in a range of social and health settings. These autonomous machines can take on various forms and shapes and interact with humans using social behaviors and rules. They are being studied and introduced in psychosocial health interventions, including mental health and rehabilitation settings, to provide much-needed physical and social support to individuals. In my doctoral thesis, I aimed to explore how humans self-disclose and express their emotions to social robots and how this behavior can affect our perception of these agents. By studying speech-based communication interactions between humans and social robots, I wanted to investigate how social robots can support human emotional well-being. While social robots show great promise in offering social support, there are still many questions to consider before deploying them in actual care contexts. It is important to carefully evaluate their utility and scope in interpersonal communication settings, especially since social robots do not yet offer the same opportunities as humans for social interactions.

My dissertation consists of three empirical chapters that investigate the underlying psychological mechanisms of perception and behaviour within human–robot communication and their potential deployment as interventions for emotional well-being. Chapter 1 offers a comprehensive introduction to the topic of emotional well-being and self-disclosure from a psychological perspective. I begin by providing an overview of the existing literature and theory in this field. Next, I delve into the social perception of social robots, presenting a theoretical framework to help readers understand how people view these machines. To illustrate this, I review some of the latest studies on social robots in care settings, as well as those exploring how robots can encourage people to self-disclose more about themselves. Finally, I explore the key concepts of self disclosure, including how it is defined, operationalized, and measured in experimental psychology and human–robot interaction research. In my first empirical chapter, Chapter 2, I explore how a social robot's embodiment influences people's disclosures in measurable terms, and how these disclosures differ from disclosures made to humans and disembodied agents. Chapter 3 studies how prolonged and intensive long-term interactions with a social robot affect people's self-disclosure behavior towards the robot, perceptions of the robot, and how it affected factors related to well-being. Additionally, I examine

the role of the interaction's discussion theme. In Chapter 4, the final empirical chapter, I test a long-term and intensive social robot intervention with informal caregivers, people living with considerably difficult life situations. I investigate the potential of employing a social robot for eliciting self-disclosure among informal caregivers over time, supporting their emotional well-being, and implicitly encouraging them to adapt emotion regulation skills. In the final discussion chapter, Chapter 5, I summarise the current findings and discuss the contributions, implications and limitations of my work. I reflect on the contribution and challenges of this research approach and provide some future directions for researchers in the relevant fields. The results of these studies provide meaningful evidence for user experience, acceptance, and trust of social robots in different settings, including care, and demonstrate the unique psychological nature of these dynamic social interactions with social robots. Overall, this thesis contributes to the development of social robots that can support emotional well-being through self-disclosure interactions and provide insights into how social robots can be used as mental health interventions for individuals coping with emotional distress.

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Acknowledgements

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Author's Declaration

I declare that, except where explicit reference is made to the contribution of others, that this thesis is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

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Research Output

Publications and pre-prints related to the empirical chapters of this thesis

Chapter 2:

- Laban, G., Morrison, V., & Cross, E. S. (2020). Let's Talk About It! Subjective and Objective Disclosures to Social Robots. In *Companion of the 2020 acm/ieee international conference on human-robot interaction* (p. 328–330). Cambridge, United Kingdom: Association for Computing Machinery. Retrieved from `https://doi.org/10.1145/3371382.3378252` doi: 10.1145/3371382.3378252

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Chapter 3:

- Laban, G., Kappas, A., Morrison, V., & Cross, E. S. (2021a). Protocol for a Mediated Long-Term Experiment with a Social Robot. *PsyArXiv*. Retrieved from `https://psyarxiv.com/4z3aw/` doi: 10.31234/OSF.IO/4Z3AW

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Chapter 4:

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Other work related to this thesis

- **A summary of this dissertation, submitted and accepted for participation in the 2022 doctoral consortium of the international conference on Affective Computing and Intelligent Interaction *ACII*:**
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- **Two sections from the paper were included (and modified) in the general introduction chapter of this dissertation:**
  Henschel, A., Laban, G., & Cross, E. S. (2021). What Makes a Robot Social? A Review of Social Robots from Science Fiction to a Home or Hospital Near You. *Current Robotics Reports*(2), 9–19. Retrieved from `https://doi.org/10.1007/s43154-020-00035-0` doi: 10.1007/s43154-020-00035-0

- **Sections from the paper were included (and modified) in the general introduction and general discussion chapters of this dissertation:**
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- **The data discussed in Chapter 2 was used for the training and testing of the deep-learning architectures described in this paper:**

Powell, H., Laban, G., George, J.-N., & Cross, E. S. (2022). Is Deep Learning a Valid Approach for Inferring Subjective Self-Disclosure in Human-Robot Interactions? In *Proceedings of the 2022 acm/ieee international conference on human-robot interaction* (pp. 991–996). IEEE Press. Retrieved from `https://dl.acm.org/doi/abs/10.5555/3523760.3523921` doi: 10.5555/3523760.3523921

Other work

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Chapter 1

General Introduction

Emotional well-being refers to the presence of positive emotions and moods, as well as the ability to manage negative emotions and stress, along with thoughts and behaviours in a way that allows for healthy functioning in daily life. It also includes the ability to set and achieve meaningful goals, to have a sense of purpose, and to feel a sense of belonging and connectedness with others. Emotional well-being is not just the absence of mental health problems or illness, it also includes the presence of positive experiences and emotions (Courtwright, Flynn Makic, & Jones, 2020; Feller et al., 2018). In recent years, there has been a growing recognition of the importance of addressing emotional well-being in global health policy. This is because emotional well-being is critical for overall health and well-being, and because poor emotional well-being is a significant burden on individuals, families, and society as a whole (Feller et al., 2018). This has been further illuminated during the recent COVID-19 pandemic, where lockdown measures have led to peak increases in depressive symptoms, anxiety, loneliness, and severe stress (Brooks et al., 2020; Stieger, Lewetz, & Swami, 2021; Tull et al., 2020).

Emotional well-being is important for social and occupational functioning, as people with high levels of emotional well-being are more likely to have successful relationships (Ermer & Proulx, 2022) and perform well at work (van Kleef, Homan, & Cheshin, 2012) and in their studies (Bücker, Nuraydin, Simonsmeier, Schneider, & Luhmann, 2018; Latorre-Cosculluela, Sierra-Sánchez, Rivera-Torres, & Liesa-Orús, 2022). Accordingly, emotional well-being might carry important implications for societal and economic development and stability (Feller et al., 2018; Moro-Egido, Navarro, & Sánchez, 2022). More specifically, emotional well-being is closely tied to physical health and overall well-being. Research has shown that people with high levels of emotional well-being are more likely to be healthy, have a better immune function, and live longer. On the other hand, people with poor emotional well-being are at an increased risk for a range of physical health problems, such as heart disease, stroke and chronic illnesses (Stewart-Brown, 1998).

Beyond physical health, people with high levels of emotional well-being tend to show fewer symptoms of poor mental health, and people with good mental health tend to report high emotional well-being (Tantam, 2014). Poor emotional well-being is often the result of or can be accompanied by *emotional distress* (Barry et al., 2020), an unpleasant emotional state that occurs when one is limited or unable to adapt to stressors and their consequences, perceived and actual (Ridner, 2004). Emotional distress can arise from various situations and stressors ranging from unexpected calamities (e.g., grief and loss, disasters, or physical or mental illness) to typical annoying daily events (Anisman & Merali, 1999). The feeling of persistent emotional distress has a variety of mental and physical health implications (Barry et al., 2020) ranging from psychiatric disorders and psychopathologies (e.g., depression and anxiety disorders) (G. W. Brown, 1993) to immune system dysfunction (Herbert & Cohen, 1993).

Various socio-contextual and psychological factors can enhance one's well-being. The *six-factor model of psychological well-being* explains that emotional well-being is attained by achieving a state of balance affected by both challenging and rewarding life events in six socio-contextual and psychological factors. These include self-acceptance, positive relationships with others, autonomy, environmental mastery, a feeling of purpose and meaning in life, and personal growth and development (Ryff, 1989; Ryff & Keyes, 1995). Another framework by Connell, Brazier, O'Cathain, Lloyd-Jones, and Paisley (2012) identified six domains of quality of life that are crucial for positive mental health within emotional well-being. These domains include well-being and ill-being, control, autonomy and choice, self-perception, belonging, activity, and hope and hopelessness. People achieve a state of emotional balance within these different areas of life (see Connell et al., 2012; Ryff, 1989, 1995; Ryff & Keyes, 1995) by having a good capacity for *emotion regulation*. These are a set of internal and external processes and techniques that involve monitoring, assessing, and modifying one's state behaviour or cognition in a given situation (Gross, 1998). Hence, people's emotional well-being is typically enhanced when being able to respond to ongoing demands and stressors when experiencing a range of emotions in a socially acceptable and sufficiently adaptable way to allow for spontaneous reactions, while being able to postpone spontaneous emotional reactions, when necessary, as deemed inappropriate given the context (Koole, 2009; Leventhal, Leventhal, & Contrada, 2007).

Beyond self-regulating emotions in an intrapersonal way, people often engage in various forms of interpersonal activities and behaviours to regulate their emotions and enhance their emotional well-being (Barthel, Hay, Doan, & Hofmann, 2018). People normally wish to be close to others, and research explains that it often positively affects people's emotional well-being (Hofmann & Doan, 2018). A famous neuroimaging experiment by Coan, Schaefer, and Davidson (2006) showed that holding hands with an intimate partner relieved subjects' anxiety in response to anticipated threats and that the level of relief correlated positively with subjective perceptions of relationship quality. This has been replicated, showing that proximity and touch are associated with increased interpersonal closeness also within non-romantic dyads (Prause, Siegle, & Coan, 2021). Accordingly, the *social baseline theory* explains that social proximity to other humans is associated with attenuated cardiovascular, hormonal, and neural responses to threat, as well as longevity and physical health. In other words, the presence of others helps individuals to conserve efforts and resources when socially regulating emotion. Hence, the human brain relies on having numerous different types of relationships to coordinate mental processes in order to maintain positive emotional and physical well-being (Beckes & Coan, 2011; Coan et al., 2006). This is evidenced in different human social behaviours that are aimed at connecting them to others for enhancing their well-being. For example, people often seek the *social support* of others when dealing with poor emotional well-being (Marroquín, 2011; Uchino, 2004). This sort of interpersonal act of support can be emotional, seeking to be treated with empathy, affection, love, trust and acceptance by others (Langford, Bowsher, Maloney, & Lillis, 1997; Slevin et al., 1996), or the support can be of companionship when seeking to be provided with a sense of social belonging (Wills, 1991).

Finally, people engage in various *interpersonal communication* behaviours to maintain their emotional well-being (Coan, 2012; Rimé, 2009; Zaki & Williams, 2013). Interpersonal communication holds a unique and important role in people's emotional well-being as it is the process by which people create, transmit, and interpret social messages (Segrin, 2014). It is a social space for disclosing and sharing about one's experiences, quality of life and well-being, expressing emotion, and being informed about others' emotions. Accordingly, social communication behaviours like self-disclosure can have a meaningful effect on one's emotional state (Segrin, 2014; Segrin & Taylor, 2007).

1.1 Why do we self-disclose, and how does it make us feel?

Self-disclosure is a communication behaviour aimed at introducing and revealing oneself to others, and it plays a key role in building relationships between two individuals (Jourard & Lasakow, 1958; Pearce & Sharp, 1973). Self-disclosure can be perceived as a complicated and dynamic social process that facilitates relationships and improves bonding (Altman & Taylor, 1973; Derlega, Harris, & Chaikin, 1973). People tend to disclose thoughts and feelings with others, especially when experiencing unique and/or challenging life events (Gable, Reis, Impett, & Asher, 2004). Self-disclosure thus serves an evolutionary function of strengthening interpersonal relationships but also produces a wide variety of health and well-being benefits, including coping with stress and traumatic events and eliciting help and support from those one discloses to (Frattaroli, 2006; Frisina, Borod, & Lepore, 2004; Kennedy-Moore & Watson, 2001).

One of the most important factors and facilitators of self-disclosure is *reciprocity*, a response or reaction from a conversation partner that can encourage or attenuate the level of disclosure (Derlega et al., 1973) and the relationship in general (Altman & Taylor, 1973). Reciprocity is an important interpersonal dynamic for regulating self-disclosure (Hosman, 1987) and can be expressed with different verbal and non-verbal behaviours that convey involvement in an interaction (Argyle & Dean, 1965; Firestone, 1977). Throughout a conversation, both parties implicitly interpret and react to each other's disclosures, attributing values to the breadth and depths of the disclosures for balancing and regulating their own disclosures and eventually achieving an equilibrium of reciprocal self-disclosure. When equilibrium is not achieved and the level of self-disclosure does not correspond with expectations, it can damage the relationship. Therefore, self-disclosure can feel involuntary or unnatural, and it could be perceived as invasive, abnormal, uncomfortable, and at times, even unethical (Altman & Taylor, 1973; Archer & Berg, 1978; Derlega et al., 1973).

However, people often self-disclose for different emotional reasons that extend social norms and the establishment and maintenance of interpersonal relationships. People are influenced by their moods and daily events and tend to self-disclose positive information when experiencing a positive mood or positive events (Forgas, 2011). For example, the concept of *capitalization* explains the interpersonal process of disclosing positive events to close others, which has been linked to individual and relationship well-being (Langston, 1994). When engaging in capitalization, people disclose positive information to enhance their level of positive affect, and in turn experience lower emotional distress and increased intimacy (Gable & Reis, 2010). This has been studied further, demonstrating that the sharing of positive moods and life events has shown positive benefits to both the sender and the receiver, and has been associated with increased daily positive affect and life satisfaction (Gable et al., 2004), increased relationship satisfaction and feelings of trust (Donato, Pagani, Parise, Bertoni, & Iafrate, 2014; Gable et al., 2004; Otto, Laurenceau, Siegel, & Belcher, 2015), increased self-esteem and decreased loneliness (Reis et al., 2010), and decreased negative affect (Gable & Reis, 2010). Interestingly, previous studies suggest that even when experiencing negative life events (e.g., coping with a chronic illness like cancer), engaging in capitalization and sharing positive emotions and events with intimate partners enhances relationship well-being independently of sharing bad news (e.g., Otto et al., 2015). People might also use self-disclosure to express and monitor negative emotions when experiencing negative moods, as well as when being distressed, anxious, and fearful (Ignatius & Kokkonen, 2012; Rimé, 2009; Rimé, Finkenauer, Luminet, Zech, & Philippot, 1998). For example, when engaging in *co-rumination* people extensively discuss and revisit problems, speculating about problems and self-disclosing particularly negative feelings (Rose, 2002). Another similar behaviour would be *emotional venting*, verbalizing an emotion for experiencing an emotional recovery and 'getting it off the chest' (Zech, Rimé, & Nils, 2004). Engaging in these behaviours is significantly associated with cognitive traits related to anxiety (Carlucci, D'Ambrosio, Innamorati, Saggino, & Balsamo, 2018), and while people do not immediately recover from their emotional experiences, they report more subjective benefits compared to people who do not engage in self-disclosing about negative emotions and events (Zech & Rimé, 2005). Furthermore, it has been shown that engaging in co-rumination is positively linked with friendship closeness, perceptions of relationship quality, and even greater job satisfaction (Haggard, Robert, & Rose, 2011).

The tendency to self-disclose due to personal experiences and emotions and not due to typical reciprocal norms can be further explained by the *social exchange theory* (Homans, 1958, 1961), addressing that relationships are formed through the interplay of cost and reward while comparing alternatives. With self-interest and interdependence as the basic features of an interaction, two entities hold a certain value and develop a relationship following the exchange of value. For subjective self-interests (i.e., psychological, emotional, social or economic needs), an exchange is perceived as a social behaviour with a potential social, emotional or economic outcome (Ekeh, 1974; Homans, 1961; Lambe, Wittmann, & Spekman, 2001; Lawler, 2001; Lawler & Thye, 1999). Therefore, people with certain psychological needs, positive or negative, would use self-disclosure to receive a certain reward or achieve a desired outcome from an interaction party (Worthy, Gary, & Kahn, 1969). Previous studies report that when experiencing illness, people often prefer to disclose and talk about it with people that add positive value to their experience (e.g., other patients, a psychologist, a consultant, a physiotherapist, a family medical doctor, and even their best friend), rather than family members that might get worried and transfer negative emotion to them (Herbette & Rimé, 2004). Thus, people might self-disclose for the exchange of a variety of reasons, some might be fully materialistic or subjective, like fame, popularity, novelty and curiosity (Lambe et al., 2001; Lawler, 2001; Lawler & Thye, 1999). Yet, in interpersonal settings, this could be seeking the recognition of one's emotion, empathy, advice, recommendation, or even just aspiring to be heard. In fact, previous research highlights the importance of feeling listened to, and how it might affect different factors of emotional well-being like feelings of loneliness (Itzchakov, Weinstein, Saluk, & Amar, 2022) and perceptions of burden (Itzchakov, Weinstein, & Cheshin, 2022).

Accordingly, it appears that engaging in self-disclosure can support emotional well-being via the ability to provide and receive support and improve mood and offer a comfortable setting for concealment, sharing feelings, and regulation of emotions (Coan, 2012; Kahn & Cantwell, 2016; Kahn & Garrison, 2009; Kahn & Hessling, 2001; Rimé, 2009; Zaki & Williams, 2013), and can have a positive impact on mental and physical health (Derlega, Winstead, Lewis, & Maddux, 1993). The *map of interpersonal regulation* by Zaki and Williams (2013) explains that people might use self-disclosure as different *intrinsic regulatory processes* (i.e., being the sender in a self-disclosure relationship) that can have different goals which are response-dependent or independent. When engaging in *intrinsic response-dependent regulation* one might engage in self-disclosure to a conversation partner when seeking feedback that will support their regulatory attempts, like seeking an emphatic response or confirmation (Zaki, 2020; Zaki & Williams, 2013). Previous research stresses that seeking support and concealment via disclosure can have positive effects on people's mood and helps them to cope with emotional events (e.g., Kahn & Cantwell, 2016; Kahn & Hessling, 2001; Nils & Rimé, 2012). When engaging in *intrinsic response-independent regulatio*n via self-disclosing to others, one will seek a channel for disclosure regardless of a potential response or feedback. Accordingly, the mere act of disclosure contains certain psychological components that can affect regulatory success. When sharing with others just for the sake of disclosing emotions and feelings, one might be engaged in appraising their own emotions and experiences and damping the intensity of the emotional experience (Zaki & Williams, 2013). This sort of strategy is also known as *affect labelling*, a simple and implicit emotional regulation technique aimed at explicitly expressing emotions, or in other words - putting feelings into words (Kircanski, Lieberman, & Craske, 2012; Lieberman et al., 2016; Torre & Lieberman, 2018). Accordingly, people use self-disclosure for emotional introspective processes, self-reflecting on their emotional experiences, as well as past behaviours and actions (Tamir & Mitchell, 2012). These sorts of self-disclosure behaviours are found to be highly useful for coping with emotional distress (Kircanski et al., 2012; Kross, Ayduk, & Mischel, 2016; Lieberman, Inagaki, Tabibnia, & Crockett, 2011; Lieberman et al., 2016; Torre & Lieberman, 2018; Tamir & Mitchell, 2012) and is a meaningful act of mindfulness (Creswell, Way, Eisenberger, & Lieberman, 2007). A similar example is James Pennebaker's *writing disclosure paradigm* (see Pennebaker, 1997; Pennebaker & Beall, 1986) which helps people to facilitate their emotions when writing about their own experiences. Pennebaker's paradigm (Pennebaker, 1997; Pennebaker & Beall, 1986) has been validated and found to have short- and long-term effects, including reduced blood pressure, improved mood, and reduced depressive symptoms, as well as long-term positive physical outcomes such as improved memory, improved work performance, and more (Baikie & Wilhelm, 2005).

Nevertheless, various socio-emotional factors might affect the extent to which people self-disclose, and even enhance self-disclosure avoidance. In organizational settings, for example, people tend to avoid self-disclosure and emotional expression in general for practical reasons, thinking that it might lead to a negative evaluation by colleagues with some potential to lose control over the situation (Cheshin, 2020; Steele, 1975). This reflects the general society-wide perspective of self-disclosure as a sign of weakness, exhibitionism, or mental illness, especially when these disclosures are of intimate content (Egan, 1970; Goffman, 1959). Furthermore, while self-disclosure tends to facilitate relationships, in a variety of contexts (e.g., healthcare, psychotherapy, and within organisations) individuals might try to avoid the establishment of new intimate relationships with others by talking about themselves (Egan, 1970). The social context of disclosure might position the speaker in a fragile place, requiring certain adaptability and considering the social consequences of the disclosure, including the judgment of others (Jourard, 1968). This is highly present due to the fear of *shame* and *stigma* when engaging in self-disclosure and sharing personal, and maybe even sensitive matters (Smart & Wegner, 2000). This can be evidenced when patients are asked to disclose information to healthcare providers such as medical doctors (Beckman & Frankel, 1984; Naldemirci, Britten, Lloyd, & Wolf, 2020; Senteio & Yoon, 2020), or when engaging in psychotherapy and being requested to share sensitive information. Patients might draw back and hold to that information due to the fear of being judged and viewed negatively (Farber, 2006).

The *Emotions as Social Information* (EASI) *Model* (Van Kleef, 2009) suggests that *emotional expression* (i.e., verbal or non-verbal behaviour that communicates an emotional state or attitude and can be intentional or unconscious; Shariff & Tracy, 2011) serves a social communication function. It proposes that emotions are not just personal experiences, but also convey information about the individual's internal state and intentions to others. The model proposes that emotions are universal and can be recognized by others through facial expressions, body language, and vocal cues, allowing for social interaction and coordination. More specifically, the model explains that emotional expression may affect the observers' behaviour by triggering inferential processes and/or affective reactions in them (Van Kleef & Côté, 2022). In the context of self-disclosure, people might have a greater likelihood of self-disclosing when they believe that the person they are disclosing to is likely to provide them with the emotional feedback that they seek, but may avoid self-disclosure if they believe that the person they are interacting with is not likely to provide them with the emotional feedback that they need. This may be because the person is perceived as uninterested, unapproachable, or untrustworthy, or when perceiving a conversational partner's emotional expressions as judgmental, negative, or even threatening. Hence, self-disclosure avoidance could be used as an emotion regulation technique for avoiding the emotional expression of others (Rosenfeld, 1979), especially when experiencing low mood (Kahn & Garrison, 2009) or feeling insecure (Mikulincer & Nachshon, 1991). Despite social norms of displaying affect (Matsumoto, 1990), emotional responses to stimuli (like emotional expressions) are often the initial impulsive reaction of a social being. They can happen without thorough perceptual and cognitive processing and are more certain and faster than cognitive evaluations (Zajonc, 1980). Therefore, it could be that *robots* and *artificial agents* which are automated non-human entities that can control their expressions via computing, mechanics, and design, and are objectively perceived as objects (Cross & Ramsey, 2021), could avoid some of the socio-emotional barriers to self-disclosure.

1.2 What are social robots? And what makes a robot social?

A robot (which is not particularly social) is a programmable, multifunctional manipulator designed to move material, parts, tools or devices through variable programmed motions for the performance of a variety of tasks (International Standard Organization, 2012). The concept of robots that have a social (*anthropomorphic* or *zoomorphic*) appearance or behave in a social (human-like or animal-like) way was prominent in post-modern science fiction literature, art, and cinema (Thalmann, 2022). Yet, the widely used definition for *social robots* in applied (and not fictional) settings was coined only in the last century, defined as autonomous machines that interact and communicate with humans or other agents by following social behaviours and rules relevant to the specific role for which they have been designed (Breazeal, 2003). Social robots are often expected to perform a variety of tasks in social contexts and settings, or in the form of social interaction. These tasks can be as simple as moving objects, to complex social tasks that require expressive communication (Leite, Martinho, & Paiva, 2013). Thus, social robots are gradually being introduced in different social settings such as commerce and services, health care, education, and even in people's households (Henschel, Laban, & Cross, 2021). Accordingly, robots can take on different roles and shapes, but certain factors differentiate between common industrial machines and social robots.

When making first impressions people might look for physical and visual cues in one's appearance to establish a *social perception* as these are highly accessible cues (Zebrowitz & Montepare, 2008). Due to previous knowledge and our experience in the world, we tend to make assumptions regarding one's role in the world and form a social perception based on these visual features (Evans, 2008). When perceiving non-human objects in the world people would also look for visual stimuli to further understand it, and therefore objects' appearance tends to follow the concept of *"Form Follows Function"* (Sullivan, 1896), which states that an object's design (originally addressed to buildings) should be determined by its intended purpose and function (Papanek, 1985). Accordingly, the physical appearance features of robots are important features users use to classify robots and understand their intention and use – whether it is social or not. Users look at design features such as shape and *embodiment* (i.e., the location and the character of the body in the world, and how this body structures and enables experience; Cromby, 2014). Thus, robots are often designed and engineered to convey their purpose and capabilities via the manipulation of visual stimuli. Industrial (or, simply non-social) robots are ultimately engineered and designed according to the *ergonomic* (i.e., the processes of designing and arranging products and systems to fit their users and/or their hosting organization; Wickens, Gordon, Liu, & Lee, 2013) requirements of the industrial task (e.g., moving materials or assembling parts) like safety, efficiency, human operation, as well as considering related mechanical considerations (Gualtieri, Rauch, Vidoni, & Matt, 2020). While these factors would still be considered important for developing and designing a social robot, ergonomic factors and requirements related to the social nature of the task or the social settings that the robot is aimed to be introduced in would be crucial considerations. Accordingly, social robots are often designed with principles of *cognitive ergonomics* in mind, which are concerned with mental processes during people's interactions with social robots, like perception, attention, memory, reasoning, decision-making, learning, and motor responses among others (McLeod, 2015). Different features of the design (c.f., layout and elements), system (c.f., modality and robotic behaviour), performance (c.f., success and failure), and implementation (c.f., organizational measures) are manipulated to simulate cognitive processes (e.g., perception and reasoning) that would affect the social perception of social robots in a variety of social situations (e.g., communicating, learning, playing) and social settings (e.g., education, health care, the household) (Gualtieri, Rauch, & Vidoni, 2021; Gualtieri, Fraboni, De Marchi, & Rauch, 2022).

These features are being used as *affordances*, clues to the ways that people understand and negotiate technology in everyday lives (Gibson, 1977, 2014). These clues provide individuals with visual means to establish a relationship between an organism and its environment. *Perceived affordances* (Norman, 1999) in the robot's design support users to clearly understand the robot's capabilities without needing any further explanation (e.g., a robot with legs should be able to walk, or a robot with arms should be able to carry stuff). More specifically related to social robots (and differentiating these from non-social robots) are *social affordances* (Gaver, 1996). These are clues for perceived opportunities for social interaction that are present in the environment, addressing the ways in which robots are designed and programmed to be perceived as social entities and to invite social interactions. It can include properties like the robot's appearance, movement, and behaviour, which can influence how people perceive and interact with the robot. Accordingly, it allows users to attribute social qualities to robots (e.g., friendliness, warmth, empathy), experience social elements related to the robot (e.g., trust, acceptance, enjoyment), and react socially towards robots (e.g., talk, learn from, seek companionship) (Awaad, Kraetzschmar, & Hertzberg, 2015; Gualtieri et al., 2021, 2022). For example, a robot with a *humanoid* (i.e., a robot resembling a human body in shape; Siciliano & Khatib, 2018) appearance and expressive movements may be perceived as more social, approachable, and interactive than a robot with a more mechanical appearance (i.e., *product-oriented*; Kwak, Kim, & Choi, 2014) and limited movements (c.f., Kwak, 2014; Prakash & Rogers, 2015).

Beyond usability features of social robots (i.e., affordances), it is important to consider that the quality of being social is predominantly of living organisms (Gosling & John, 1999). Therefore, when we attribute robots with social qualities, we could be looking for social traits that are common across social living things – humans or animals (Argyle & Little, 1972), depending on the robot's role. Human observers often pick up information from one's appearance and behaviour in order to interpret social features and attribute social meaning to the interaction partner (Ambady, Bernieri, & Richeson, 2000). The application of this idea in interactions with artificial agents (like social robots) is conveyed in the "*Computers as Social Actors*" (CASA) paradigm (Nass, Steuer, & Tauber, 1994). This is a theoretical framework explaining that people tend to attribute social characteristics, such as intentions and emotions, to computers, artificial agents, and other technology. This is based on the idea that people interact with technology in much the same way as they do with other people, and therefore perceive the technology as having similar characteristics. When following the social affordances of social robots (as well as other artificial agents) people tend to mindlessly attribute social characteristics to these agents and perceive and react to these accordingly. This theory has informed the design of social artificial agents to enhance trust, social interaction quality, and rapport building with robots and other artificial agents (e.g., Meyer, Miller, Hancock, de Visser, & Dorneich, 2016; Xu, 2019). Moreover, the cognitive process of observing a robot in a social context is expected to be similar to the process of observing another social being (human or animal) because of the way our brains are wired to process social information. Our brains have evolved to be highly attuned to *social cues* that signal the intentions and emotions of other beings (D. J. Greene & Zaidel, 2011; Hadders-Algra, 2022; Leppänen & Nelson, 2009; Zaki, 2013). These are nonverbal or verbal behaviours, like facial expressions, body language, making eye contact, nodding, vocal cues, and using gestures, that people use to communicate information and convey meaning in social interactions (Adams, Albohn, & Kveraga, 2017). When we observe a social entity, such as a human, animal or robot, several brain regions become active in the process of *social cognition* (Zaki, 2013).

This process begins with the *fusiform gyrus*, which is a brain region associated with facial recognition that is reliably activated when we look at faces (Iidaka, 2014; Kanwisher, McDermott, & Chun, 1997), whether human or robotic (Gobbini et al., 2011; Rauchbauer et al., 2019). This is followed by the activation of the *superior temporal sulcus*, which is associated with interpreting social cues provided by movement and posture for understanding social actions (Deen, Koldewyn, Kanwisher, & Saxe, 2015; Shultz, Lee, Pelphrey, & Mccarthy, 2011), as well as language perception (Beauchamp, 2015; Deen et al., 2015). As we observe a social being, the *amygdalae*, which process emotional information, also become active, allowing us to interpret the emotions of others (Amunts et al., 2005; Baxter & Croxson, 2012; Maren, 1999). The *inferior parietal lobule*, which is involved in understanding others' intentions, is activated next, helping us to infer what the social entity is thinking or feeling (Fogassi et al., 2005; Patri et al., 2020; Rizzolatti, Ferrari, Rozzi, & Fogassi, 2006), also when this entity is a robot (Chaminade et al., 2010; Cross et al., 2012; Cross, Riddoch, et al., 2019; Rauchbauer et al., 2019). The *inferior frontal gyrus*, which is associated with speech processing (among other things), also becomes active, allowing us to understand verbal and nonverbal social cues of both humans (Greenlee et al., 2007; Rogers & Davis, 2017) and robots (Di Cesare, Vannucci, Rea, Sciutti, & Sandini, 2020; Hogenhuis & Hortensius, 2022; Rauchbauer et al., 2019). Finally, the *temporo-parietal junction* and the *medial prefrontal cortex*, which assists with *theory of mind* (Premack & Woodruff, 1978) processes (i.e., the capacity to understand others by ascribing mental states to them; Apperly & Butterfill, 2009; Baron-Cohen, 1991), is activated when we try to infer the mental states of others (Krause, Enticott, Zangen, & Fitzgerald, 2012; Saxe & Wexler, 2005; Saxe & Kanwisher, 2004), including robots (Krach et al., 2008; Özdem et al., 2017; Rauchbauer et al., 2019). Through this process, our brain allows us to understand the social cues provided by the social being and make inferences about its intentions, emotions and mental states. While these brain regions have been documented to serve additional functions in various neurocognitive processes, the roles outlined here specifically pertain to social cognition within the context of human–robot interaction (HRI).

Therefore, we tend to interpret the appearance and behaviours of robots in terms of human-like (or animal-like, depending on the robot) characteristics such as emotions, intentions, and mental states (Hortensius, Hekele, & Cross, 2018). However, it is worth noting that the level of activation of these regions is not the same when observing a robot as when observing a human, as the level of complexity and realism of the robot can affect the activation of these regions, among several other important factors (see Cross, Hortensius, & Wykowska, 2019; Cross & Ramsey, 2021; Hortensius & Cross, 2018, for further discussion). Moreover, the likelihood of attributing social qualities and mental states to robots is influenced by variety of other factors, including the age and motivation of the human observer, as well as the behavior, appearance, and identity of the robot (see review by Thellman, De Graaf, & Ziemke, 2022). Therefore, we should further consider the different factors that shape our social perception and social behaviour when interacting with robots.

1.3 Why do we perceive and interact with some robots more socially than with others?

Physical face-to-face interactions convey information through unrestricted verbal expression, gestures and facial displays, and through continuous collaboration between both parties of the interaction. The presence and interaction of these features together are unique to physical face-to-face interactions, whereas other modes of interaction are limited in extracting and demonstrating a wide range of social cues (Bavelas, Hutchinson, Kenwood, & Matheson, 1997). In the context of information technologies, the *media richness theory* (MRT; Daft & Lengel, 1986) explains that a communication medium's ability to reproduce the information sent through it is driven by its ability to communicate a complex message adequately. Hence, social interactions typically perform better through media with the capacity to convey richer social cues, like gestures and body language (Carlson & Zmud, 1999; Daft & Lengel, 1986). This idea emphasizes the importance of *social* *embodiment* (i.e., the states of the body, such as postures, arm movements, and facial expressions that arise and are manipulated during social interactions and play a central role in social information processing; Barsalou, Niedenthal, Barbey, & Ruppert, 2003) and *physical embodiment* (i.e., having a physical body or physical instantiation; Ziemke, 2003) in interactions with artificial agents (and particularly in human–robot interactions). The theory of *embodied cognition* explains (in the context of social cognition) that the body has an active and significant role in understanding an agent's mind and cognitive capacities (Anderson, 2003; A. Clark, 1997). When an object (for the scope of this thesis, an artificial agent) is embodied, it takes a physical representation in the world that describes its capabilities, roles, and features. On the other hand, when the object is *disembodied*, it takes an abstract representation that might limit our understanding of it (Pfeifer & Scheier, 2001). As humans, we find it easier to understand similar bodily experiences to our own embodied experiences (Byrne, 1961; Johnson, 2015; Meltzoff, 2007; Meltzoff & Prinz, 2002).

When interacting with artificial agents, people perceive and respond to their reciprocated behaviour in different ways depending on the agents' embodiment (Deng, Mutlu, & Mataric, 2019; Foster, 2019; Fridin & Belokopytov, 2014; K. M. Lee, Jung, Kim, & Kim, 2006; Luria, Hoffman, & Zuckerman, 2017; Xu, 2019). People tend to perceive agents more socially when embodied agents convey socially-relevant information through body language (Beck, Yumak, & Magnenat-Thalmann, 2017b; Foster, 2007, 2019) and when the agent can express itself using a wide range of social cues (André, 2014; Deng et al., 2019; Foster, 2019; Vinciarelli, Pantic, Bourlard, & Pentland, 2008), like voice (e.g., Cambre & Kulkarni, 2019; Skantze, Oertel, & Hjalmarsson, 2013; Voorveld & Araujo, 2020; Xu, 2019), gaze (e.g., Babel et al., 2021; Scandola, Cross, Caruana, & Tidoni, 2023; Skantze et al., 2013; Kontogiorgos, Skantze, Abelho Pereira, & Gustafson, 2019), facial expression (e.g., C. Chen et al., 2019; Rawal & Stock-Homburg, 2022), or even touch (e.g., Burns, Lee, Seifi, Faulkner, & Kuchenbecker, 2022; Geva, Uzefovsky, & Levy-Tzedek, 2020; Geva, Hermoni, & Levy-Tzedek, 2022; Hirano et al., 2018; Sefidgar et al., 2016; Shiomi, Nakata, Kanbara, & Hagita, 2020; Willemse & van Erp, 2019). Moreover, the effect of embodiment is even more distinct when it is physical, considering the wider variations and freedom of the agent's behaviour and reactions (J. Li, 2015). Therefore, embodied robots that utilize different social cues and are physically present may be perceived as more social and responsive than a robot that does not have these capabilities.

Nevertheless, while embodiment and the presence of a wide variety of social cues would encourage users to interact with social robots more socially, it could also hamper the interaction. The "*uncanny valley*" (Mori, 1970; Mori, MacDorman, & Kageki, 2012) is a phenomenon where a robot or other non-human entity that is almost, but not quite, human-like in appearance can cause a sense of unease or revulsion in some people. This theory suggests that as the appearance and behaviour of a robot become more human-like, people's social (as well as emotional) response to the robot becomes increasingly positive until it reaches a point where the robot is almost, but still not quite, human-like. At this point, people's social and emotional responses become increasingly negative, creating a "valley" in their social perception and response to the robot. In other words, increased (human) realism of a robotic agent does not necessarily imply acceptance (Pollick, 2010). This theory has been tested and studied in various social settings using different types of measurements (Laakasuo, Palomäki, & Köbis, 2021; Mathur & Reichling, 2016; Paetzel, Peters, Nyström, & Castellano, 2016; Reuten, van Dam, & Naber, 2018; Tinwell, Grimshaw, Nabi, & Williams, 2011; Walters, Syrdal, Dautenhahn, te Boekhorst, & Koay, 2008) further explaining that people may be more likely to perceive a robot with a highly human-like appearance as uncanny or creepy. It is important to mention that some empirical research also rejects the uncanny valley hypothesis in specific features (see Pollick, 2010) like human-like motion (e.g., Piwek, McKay, & Pollick, 2014).

As the physical features of robots hold an important role in the psychology of human-robot social interaction, so too does the robot's behaviour. As social robots are aimed to answer to specific tasks and functions their behaviour can influence the way these are perceived. Scholars often describe the social behaviours of robots as social by answering to a wide set of verbal and non-verbal communication-related behaviours (Sarrica, Brondi, & Fortunati, 2020). A study by de Graaf, Ben Allouch, and van Dijk (2015) evaluated users' perspectives on the characteristics of social HRI through a longitudinal home study. They observed and identified eight main social characteristics that users described as factors for a social robot to appear as social and be accepted as a social entity in their homes. The most prominent factor was (1) the capability of *two-way interaction*, expecting a robot to be able to respond to a human in a social manner. When a robot failed to do so, people were disappointed and experienced a sense of dissonance. Hence, when a robot is programmed to initiate social interactions (c.f., Satake et al., 2009; Shi, Shiomi, Kanda, Ishiguro, & Hagita, 2015), understand and respond to humans' speech or social cues (c.f., Kostavelis et al., 2019; Powell, Laban, George, & Cross, 2022; Abbasi et al., 2022), provide feedback (see review A. Axelsson, Buschmeier, & Skantze, 2022), engage in turn-taking (see review Skantze, 2021), collaborate (see Kontogiorgos & Pelikan, 2020), adapt (Churamani, Kalkan, & Gunes, 2020; Churamani, Axelsson, Caldir, & Gunes, 2022) and show proactive engagement (c.f., Rivoire & Lim, 2016), it may be perceived as more social than a robot that does not have these capabilities. Nonetheless, the social behaviour of robots extends from merely communication abilities as evident from the additional user perceptions of social robots that were addressed in de Graaf et al. (2015) results. Users described the need for robots to share the same environment as them (be physically embodied or embedded), and to: (2) *display thoughts and feelings*; (3) be *socially aware of their environment*; (4) provide *social support* by being there for them (like their friends); and (5) *demonstrate autonomy*. Participants also raised the concepts of (6) *cosiness*; (7) *similarity to self*; and (8) *mutual respect*. However, these latter three concepts were mentioned fewer times than the previous five concepts.

The results of de Graaf et al. (2015) highlight that social perception of robots revolves around *robotic social intelligence* (Dautenhahn, 2007) – the ability to act as a social actor in a social environment. As described in de Graaf et al. (2015) study, users' expectations were influenced by their relationships with other social actors (i.e., their friends). Participants repeatedly compared the robot in that study to their friends, dwelling on the fact that the robot's lack of social capabilities meant that it would be unlikely to become an actual "friend". Or in other words, it would be unlikely to communicate with this agent in a socially meaningful way. It is of note, however, that these definitions rarely address the context of the interaction, whose importance is underscored by the findings of de Graaf et al. (2015) as social robots are often being introduced as submissive to humans answering their needs, rather than equals as other humans in social relationships (Darling, 2021). This discrepancy has been noted in other user studies as well. For example, Dautenhahn and colleagues (2007) show that participants in their studies did not see robots as companions or friends, but rather as useful household servants. Dereshev, Kirk, Matsumura, and Maeda (2019) interviewed long-term users of the humanoid robot Pepper (SoftBank Robotics). These users had been living and interacting with Pepper for long periods of time, ranging from 8 months to more than 3 years. Similarly to de Graaf et al. (2015) findings, Dereshev and colleagues (2019) results stress that users were often disappointed when Pepper could not engage in a two-way interaction and its ability to provide adapted and relevant feedback was limited. Users often expect a certain degree of *behavioural reciprocity*, when interacting with humans (see Archer & Berg, 1978; Becker, 1986; Derlega et al., 1973; Hosman, 1987), and accordingly, when interacting with social artificial agents like social robots (see Dereshev et al., 2019; Zonca, Folsø, & Sciutti, 2021).

Behavioural reciprocity is a response or reaction from an interaction partner that can encourage or attenuate the interaction (Derlega et al., 1973) and the relationship in general (Altman & Taylor, 1973). It includes using a variety of social cues during an interaction, like eye contact, interpersonal distance, gestures of affiliation (such as nods, sounds, and mimicry), touch, posture, and hand gestures (Argyle & Cook, 1976; Argyle & Dean, 1965; Patterson, 1973). Throughout an interaction, both parties interpret and react to each other's behaviours and disclosed content. They attribute meaning to these behaviours and use it to balance and regulate their behaviour to achieve an equilibrium by reciprocating behaviours. When the equilibrium is not balanced, individuals tend to socially withdraw from the interaction (Argyle & Dean, 1965). Accordingly, humans would expect a robot to show reciprocity in their behaviour, and if an equilibrium is not achieved it might affect the extent to which a robot is perceived as social, and the extent to which individuals socially interact with it.

The role of reciprocity sets the stage for one more behavioural factor that is crucial for the perception and behaviour in social interactions with robots, this is the *novelty effect* (Smedegaard, 2019, 2022). The novelty effect is a common problem in social robotics, and long-term studies have often found a reduced engagement with various robotic platforms over time (Dautenhahn, 2007; Leite et al., 2013). As social robots are a new emerging technology that is exciting for most, users often have higher expectations of social robots and experience dissonance when a social robot's performance is not in line with their expectations. Accordingly, when users interact with robots over time, they tend to perceive it as being less social as the interaction (or interactions) go on as their expectations of the robot are not being fulfilled (Smedegaard, 2022). Previous studies show that even household robotic devices that are not particularly social (like the Roomba vacuum cleaner) suffer from the novelty effect (Sung, Christensen, & Grinter, 2009), with users being excited about the robotic device at first and using it less as they get familiar with it. Accordingly, it should be noted that social robotic behaviour is not solely about factors of social intelligence (e.g., de Graaf et al., 2015) nor of communication abilities (e.g., Sarrica et al., 2020), but also has to do with general *competency* (i.e., the efficiency of performance; Spencer & Spencer, 1993) and *user experience* (i.e., user's perceptions of utility, ease of use, and efficiency of intelligent interfaces; Forlizzi & Battarbee, 2004; Norman, Miller, & Henderson, 1995, including social robots; see Shourmasti, Colomo-Palacios, Holone, & Demi, 2021). Like other robotic devices, a social robot should be able to complete the task it was designed and developed to complete. A previous study demonstrated that when robots are taking anthropomorphic embodiment, their failures and lack of competency are even more renounced (Kontogiorgos, Pereira, & Gustafson, 2021).

This is the intersection between a robot's visual appearance and the way it functions, as robotic appearance often provides users with affordances regarding the robotic functionality – if the robot cannot comply with users' expectations it will be perceived as incompetent (Reeves, Hancock, & Liu, 2020; Tian & Oviatt, 2021; Wiese, Metta, & Wykowska, 2017). Therefore, the occurrence of users' dissonance of robots in social settings will substantially affect the way these are perceived as social. There is, in fact, a certain dissonance that often occurs in HRIs when a person is not sure how to behave or interact with the robot, or, more importantly, when the robot's behaviour or functionality is not in line with the person's expectations or preconceived notions about robots. This dissonance has been previously termed the *social robot paradox* (Duffy & Joue, 2005). The idea of robots assisting with every aspect of daily life, as depicted in science fiction, has fuelled our imagination about the possibilities for the future (Broadbent, 2017). These ideas are even amplified when considering the physical and social affordances of robots, setting high expectations for robotic behaviour. While these fictional robots continue to be a distant vision, they have influenced our understanding and expectations of what autonomous technology could potentially achieve (Duffy & Joue, 2005; Henschel et al., 2021).

This dissonance extends from mere features of competency and user experience and occurs also when the social robot's appearance is not consistent with the behaviour it demonstrates. Similar to the uncanny valley (Mori, 1970; Mori et al., 2012) introduced previously, when a social robot is presented in a certain way that calls for social interaction (e.g., a humanoid social robot that is aimed at conversing verbally with humans) then demonstrates behaviours that are not social (e.g., the inability to hold a conversation), people often perceive it as less social and withdraw from the interaction (c.f., Gompei & Umemuro, 2015). This idea is further augmented by the *mind perception* theory (Epley & Waytz, 2010; K. Gray, Young, & Waytz, 2012). While the uncanny valley is focused mostly on the aesthetic and visual features of the robot, mind perception provides an additional approach focusing on the social role and functioning of the robot. The theory explains that people often ascribe two key and distinct dimensions of mind – "*agency*" (referring to an agent's ability to act independently) and "*experience*" (referring to an agent's ability to sense and feel") (H. M. Gray, Gray, & Wegner, 2007). Therefore, people often perceive and react to other social entities, human or non-human, based on the moral judgment of their behaviour – whether these can be responsible for their actions (i.e., demonstrating agency), and whether they can understand others and show patience (i.e., demonstrating experience). When one's actions do not answer to our definitions of social behaviour, we would be less likely to react to this agent in a social way (Epley & Waytz, 2010; K. Gray et al., 2012). Thus, a social robot would be perceived as more social when behaving in a socially moral way, following the rules and expectations of human behaviour. Previous studies show further support for mind perception via people's behaviour towards robots as well as affecting their social attitudes in different settings. For example, people are more likely to follow a robot's instructions when it asks them to participate in a task that is revocable rather than irrevocable (Salem, Lakatos, Amirabdollahian, & Dautenhahn, 2015). Another study showed that people were more likely to change their decisions in a decision-making task following advice from a robot that was presented via logical reasoning rather than via a judgmental fallacy (Polakow, Laban, Teodorescu, Busemeyer, & Gordon, 2022). Hence, when the robot's behaviour is appropriate for its role and consistent with users' social expectations of it, people may perceive and behave more socially towards it.

The importance of setting people's expectations to appropriate levels is highlighted by the story of the robot Jibo, which also serves as a cautionary tale of this point and is shared with several other social robotic companies (Hoffman, 2019). Jibo was among the first social robots developed for private consumers and was introduced in 2014 as a family robot designed to take up residence in people's homes, to establish social relationships with them and serve as a personal assistant (Breazeal, 2014; Hodson, 2014). By 2017, the company announced layoffs (Martin, 2017), sold its intellectual property and assets in 2018 (Ackerman, 2018), and by 2019, Jibo announced to its users the imminent shutdown of its servers (Heater, 2019). Nevertheless, this story too has a happy ending. In early 2020 the assets of Jibo were acquired by the Japanese telecommunications company Nippon Telegraph and Telephone (NTT) (Crowe, 2020). Interestingly, NTT decided to focus Jibo's future in health care and education. Instead of focusing on developing Jibo as a personal assistant robot that people can buy and use straight out of the box, NTT plans to market Jibo to businesses that provide certain services (such as healthcare and education) as a tool for professionals to use (Carman, 2020; NTT Disruption, 2020). Supporting this decision is NTT's assessment that Jibo will be more valuable as an enterprise product in these designated domains, rather than as a consumer product. Surveying this area more broadly, the application of social robots within care settings, and as tools to deliver health and well-being interventions, is already an emerging success story highlighting contexts and uses where social robots are successfully being deployed as autonomous assistance tools for human users (Cifuentes, Pinto, Céspedes, & Múnera, 2020; N. L. Robinson, Cottier, & Kavanagh, 2019). Therefore, despite the various limitations of social robots' social capacities (Cross, Hortensius, & Wykowska, 2019; Hortensius & Cross, 2018), limiting HRIs to specific domains (e.g., health care or education) with clear boundaries that are clearly defined and understood, would help to prevent misunderstandings and miscommunications (Henschel et al., 2021), and would ultimately affect positively on the social perception of robots.

1.4 Introducing social robots in health and care settings

Following from the previous section it remains uncontroversial that social robots do not (yet) offer the same opportunities as humans for social interactions (Cross, Hortensius, & Wykowska, 2019; Hortensius & Cross, 2018), they can nonetheless afford valuable opportunities for social engagement with human users when introduced in specific contexts, and in careful, ethically responsible ways (M. Lee et al., 2022; Villaronga, Kieseberg, & Li, 2018; Wullenkord & Eyssel, 2020). A growing evidence base documents how social robots might function as autonomous tools to support psychological health interventions (Alnajjar et al., 2019; N. L. Robinson et al., 2019) and mental health (Laban, Ben-Zion, & Cross, 2022; Scoglio, Reilly, Gorman, & Drebing, 2019), physical therapy and physical health (Assad-Uz-Zaman, Rasedul Islam, Miah, & Rahman, 2019; Y. Chen, Garcia-Vergara, & Howard, 2018; Dembovski, Amitai, & Levy-Tzedek, 2022; Feingold Polak & Tzedek, 2020; Feingold-Polak, Barzel, & Levy-Tzedek, 2021; A. Langer, Feingold-Polak, Mueller, Kellmeyer, & Levy-Tzedek, 2019; Mohebbi, 2020), and other means to amplify or support human therapeutic efforts (Cifuentes et al., 2020; N. L. Robinson et al., 2019; Scoglio et al., 2019). Moreover, social robots are being equipped with technologies such as sensors, cameras, and processors, which promote the collection of human data (such as where a person is standing, where they are looking, what they are saying, etc.) with high fidelity, as well as support on-line, on-going analysis of a human interaction partner's behaviour.

Several studies have been showing the potential introduction of social robots' behavioural change interventions, showing how robots can positively affect human behaviour also in health contexts. One such study by da Silva et al. (2018) tested an intervention for students (N = 20), aimed at encouraging their motivation to exercise through motivational interviewing, using the humanoid Nao robot (SoftBank Robotics). The results of their study demonstrated that some participants felt that the intervention increased their physical activity levels and their motivation to exercise. Interestingly, participants expressed a positive opinion of Nao as it appeared to be non-judgmental. This is a meaningful benefit of using social robots in psychosocial interventions, as these machines can overcome some of the social desirability limitations when similar interventions are operated exclusively by people. Another study that used Nao demonstrated its viability of delivering a behaviour change intervention to 26 adults, applying a motivational intervention for reducing high-calorie snack consumption (N. L. Robinson, Connolly, Hides, & Kavanagh, 2020a). This study reported a $\geq 50\%$ snack episode reduction between the beginning of the intervention and week 8, and an average weight reduction of

4.4 kg over the first 2 weeks of the treatment. Four weeks from the beginning of the intervention, participants reported an increase in their perceived confidence in controlling their snack intake and their emotional states. The results of this study demonstrate that in certain contexts and settings, social robots have the potential to autonomously behaviour change interventions. Robinson and Kavanagh (2021) also collected qualitative data addressing the subjective experiences during such interventions, reporting that participants evaluated the robot positively on its interactive nature and sociable persona. Moreover, the authors reported a similar intervention that has been tested with a clinical population (4 participants suffering from diabetes) showing the potential for using social robots for diabetes management (N. L. Robinson, Connolly, Hides, & Kavanagh, 2020b).

Social robots with more degrees of freedom in terms of their movement and behavioural repertoire can provide more advanced assistance, for example, by demonstrating complex physical movements to assist with rehabilitation, build physical fitness, and help people cope with injury and illness (A. Langer & Levy-Tzedek, 2021; Mohebbi, 2020). A study by Feingold Polak and Tzedek (2020) reported positive outcomes for a long-term upper limb rehabilitation intervention delivered via the humanoid social robot Pepper (SoftBank Robotics) for post-stroke patients in a rehabilitation facility. Moreover, clinicians and patients in this study found the intervention with Pepper to be engaging, motivating, and most importantly meeting the needs of upper limb rehabilitation. Similar work has examined how the smaller, less expensive Nao robot can also deliver physical therapy for upper limb impairment and shows similar effectiveness of this robot in rehabilitation contexts with adults (Assad-Uz-Zaman et al., 2019). Furthermore, Chen and colleagues (2018) have shown that an even more compact and simple social robot (Darwin from RobotLab, San Francisco, CA, USA) can be effectively deployed to assist children with and without cerebral palsy performing reach actions. Due to the complexity of employing such interventions with diverse populations that require specialized care approaching stakeholders is an important goal for studying and testing social robots for rehabilitation and physical support. Among the recent studies evaluating stakeholders' demands, needs and attitudes towards socially assistive robots, there are promising results from focus groups approaching stroke patients and their informal caregivers (Dembovski et al., 2022) and clinicians who treat Parkinson's disease (IwPD) as well as IwPD and their family members (Bar-On, Mayo, & Levy-Tzedek, 2021). This work further underscores the potential value and utility of embodied social robots for building physical capacity in individuals across the lifespan.

1.5 Social robots providing socio-emotional support

Previous studies have also been showing promising evidence for the emotional support social robots could be providing in a wide variety of settings. Research into the application of social robots in psychosocial health interventions highlights how social robots that take on different forms of embodiment and design can benefit different interventions. For example, robots like Paro, which take on a zoomorphic pet- or cuddly toy-like embodiment, hold value for interventions when used with appropriate target populations (e.g., Pu, Moyle, Jones, & Todorovic, 2021; H. Robinson, MacDonald, Kerse, & Broadbent, 2013), including older adults in care homes and people with cognitive impairment (e.g., dementia; see reviews Góngora Alonso et al., 2018; Koh, Felding, Budak, Toomey, & Casey, 2021; Lu et al., 2021). These can also support older adults that are suffering from mood disorders or even just feeling low due to the loneliness experienced in old age. For example, a study with 20 older adults by Chen and colleagues (2020) found that after 8 weeks of intervention using the robot Paro participants showed significant improvements in mental well-being (including decreasing rates of depression and loneliness and improving quality of life over time). These findings are further supported in the literature. A scoping review of 29 studies by Hung et al. (2019) found that previous studies using Paro provided evidence that this robot reduces negative emotions in patients, improves their social engagement, and generally promotes a positive mood, atmosphere, and quality of care experience. Moreover, these effects are grounded in people's objective experience of emotional well-being as recent studies show how interactions with these companion robots positively affect people's physiology. A study by Geva et al. (2020) documents the psychophysiological benefits of interacting with a companion robot like Paro, demonstrating that stroking Paro reduces pain perception and salivary oxytocin levels in a sample of 83 healthy adults. An additional study by this group (Geva et al., 2022) showed that part of this effect is due to the robot's interactive qualities. They found that touching (60 healthy young participants) the robot Paro induced a decrease in mild pain ratings only when the robot was activated, whereas the decrease in strong pain ratings was similar when the robot was active or off. Interestingly, they also found that the decrease in mild pain ratings was significantly greater in participants with a higher positive perception of their interaction with Paro.

Companionship is only one form of emotional support and robots with a more human-like embodiment could be more effective for delivering health interventions and providing emotional support in paradigms that require more active participation. A recent scoping review suggests that more than half (53.8 %) of the social robots used in studies between 2013 to mid-2022 focused on robots providing socio-emotional support were humanoids (Spitale & Gunes, 2022). Social robots can support people and help them improve their well-being, while also being equipped with advanced AI software to recognize people's emotions (e.g., semantic understanding, discreet emotion recognition, facial expression and movement recognition) and show affective personalized behaviour accordingly (Rhim et al., 2019; Spitale & Gunes, 2022). Some studies show how social robots could provide socio-emotional support to individuals who suffer from different mental health issues and psychopathologies and/or related symptoms (see S. C. Chen, Jones, & Moyle, 2018; Duradoni, Colombini, Russo, & Guazzini, 2021; Scoglio et al., 2019). A previously published meta-analysis of 12 studies reported a medium effect size for robot-enhanced psychotherapy, explaining that 69% of patients in control groups did worse than the average number of participants in the intervention group (Costescu, Vanderborght, & David, 2014). A recent scoping review with 30 papers that were published since 2015 showed that social robots have been studied with populations suffering from varying levels of cognitive impairments and dementia, people suffering from neurodevelopmental disorders such as autism spectrum disorder (ASD), attention deficit disorders (ADHD) and intellectual disability, as well as mental illness such as schizophrenia and depression (Guemghar et al., 2022).

For example, a mixed-method study with 180 low-income and socially isolated older adults in South Korea showed that after interacting with the humanoid social robot Hyodol for 3 months (i.e., providing reminders and guiding different exercises and recreational activities; see O. E. K. Lee & Davis, 2020), participants showed reduced depressive symptoms and improved health-related quality of life (O. E. K. Lee, Nam, Chon, Park, & Choi, 2022). Another example is a study where the social robot Nao (SoftBank Robotics) was employed to mediate a single-session loving-kindness meditation and walking meditation, oriented to counter symptoms of depression among young people (N = 142). The study reports that the social robotic interventions were successful in evoking state openness, with the former also exerting a positive effect on valence (Huang, Cheung, & Hoorn, 2022). In terms of anxiety disorders, one prominent example is a study by Matheus, Vázquez, and Scassellati (2022) with two participant cohorts (one cohort including 21 participants that were not screened for anxiety, and another cohort including 22 participants who self-reported to be treated for anxiety) that demonstrated a significant reduction in 6 anxiety measures after participating in a deep breathing intervention guided by the social robot Ommie. A previous study by Nomura, Kanda, Suzuki, and Yamada (2020) showed the benefits of employing social robots for minimising social tensions and anxieties, describing that participants with higher social anxiety tended to feel less anxious and demonstrated lower tensions when knowing that they would interact with robots in opposition to humans. A recent paper describe the benefits of employing social robots as interventions for social anxiety, stating that these could complement the support provided by clinicians. The authors explain that social robots could support people to get into therapy and maximize the effectiveness of the therapy by increasing the patients' engagement and continuing the support outside the therapy session (Rasouli, Gupta, Nilsen, & Dautenhahn, 2022). The authors also reached out to potential stakeholders (85 students) providing insights into the potential adaptability of social robots as interventions for social anxiety for this target population (Rasouli, Ghafurian, & Dautenhahn, 2022). In a previous paper (Laban, Ben-Zion, & Cross, 2022) I addressed similar benefits of using social robots for diagnosing and treating people suffering from post-traumatic stress disorder (PTSD), social robots can assist with overcoming several logistical and social barriers that trauma survivors face when required to monitor symptoms and when seeking mental health interventions.

Beyond supporting people who are suffering from clinically diagnosed psychopathologies like PTSD and anxiety, social robots could also provide emotional support via self-managed interventions to healthy individuals that might experience difficult emotional situations and stressors in their daily lives. Previous studies administered the application of social robots in emotionally supportive settings showing meaningful outcomes in terms of cognitive change and affect. A study by Bodala, Churamani, and Gunes (2021) employed the social robot Pepper (SoftBank Robotics) to deliver teleoperated mindfulness coaching to 18 participants for five weeks evoking positive responses from the participants across all sessions. Another example by M. Axelsson, Churamani, Caldir, and Gunes (2022) tested a robotic coach (Pepper, SoftBank Robotics) conducting positive psychology exercises to 20 participants in 3 sessions, showing positive mood change after participation in the robotic intervention. Robotic interventions for people's well-being are rarely taking place in people's homes and are often conducted in laboratories. One successful example is a study employing the social robot Jibo (NTT) as a positive psychology coach to improve students' psychological well-being in students' on-campus housing. The study results describe a positive effect on students' psychological well-being with positive mood change and students expressing their motivation to change their psychological well-being (Jeong et al., 2022). Finally, the following study demonstrated interesting insights regarding how social robots could support people's emotional well-being in social settings that extend the human-robot dyad. This study described positive responses from human users to a humanoid robotic head (Furhat Robotics) taking the role of a couples' counsellor, aiming to promote positive communication. It is of note that the robot also played a meaningful role in mediating positive responses (in terms of behaviour and affect) within the couples' dyadic interaction in this same study (Utami, Bickmore, & Kruger, 2017).

To summarise, the state of the art on the potential of social robots to contribute to the greater good of society, increasing research effort is being invested in this domain, and some early results speak to how robots might be able to support human psychosocial, socio-emotional, and physical function is promising. The current public health crisis has thrown into even starker contrast the value and need for not just technological solutions, but embodied technological solutions to help people stave off the different factors of emotional distress such as loneliness, stress, and negative mood (Odekerken-Schröder, Mele, Russo-Spena, Mahr, & Ruggiero, 2020; G.-Z. Yang et al., 2020). Moreover, these technologies could support individuals by being their companions (e.g., Ruggiero, Mahr, Odekerken-Schröder, Spena, & Mele, 2022), but also help them to connect with others and overcome their social and emotional barriers. Social robotics can undoubtedly contribute to improving people's quality of life, but the need remains for more methodologically rigorous and ethically sound research into how social robots might interact with humans in a sensitive, timely and nuanced manner.

1.6 Why do we self-disclose and verbally interact with robots and how does it make us feel?

Beyond the positive benefits of self-disclosure to emotional well-being that were mentioned earlier in this chapter (e.g., see Forgas, 2011), self-disclosure and verbal interpersonal communication, in general, are key features for the success of social robotic health interventions. For health interventions to succeed, they depend on open channels of communication where individuals can self-disclose their needs and emotions, from which a listener can identify stressors and respond accordingly (Colquhoun, Squires, Kolehmainen, Fraser, & Grimshaw, 2017; Wight, Wimbush, Jepson, & Doi, 2016). This is particularly important for self-help autonomous systems like social robots as human behaviour and emotions are analysed and synthesized by machines from human output, to respond and react appropriately by extracting salient information and identifying patterns and emotional states (Kappas, Stower, & Vanman, 2020). Nevertheless, engaging a robot in a reciprocal conversational interaction is a complex technical task (as discussed earlier in this chapter, within the context of behavioural reciprocity), and when self-disclosing to social robots, human users would rarely experience an equilibrium of reciprocal disclosures (Archer & Berg, 1978; Derlega et al., 1973). Following mind perception and the typical users' dissonance of social robots (that were mentioned earlier in this chapter), it can be assumed that the expectation for a reciprocal verbal engagement in HRIs when self-disclosing to a social robot might negatively affect people's experience, potentially limiting the depth and breadth of their disclosures and verbal engagement with the robot.

However, when engaging in self-disclosure towards social robots (and other artificial agents) it is theorised that people are more likely to embrace different benefits of this behaviour as a form of social exchange (see Homans, 1958; Lawler, 2001; Worthy et al., 1969) and might ignore the lack of traditional reciprocity that is accustomed between humans (Becker, 1986; Derlega et al., 1973). Hence, reciprocity in this context is thought to take place as an act of exchange. Another similar (yet, more media-centric) theoretical approach for explaining users' willingness to self-disclose to social robots is the *uses and gratification theory* (Katz, Blumler, & Gurevitch, 1973). The theory explains that media users are not passive consumers and would turn to specific media accordingly to the immediate gratifications they receive from it. Thus, in the context of social robots, users might turn to social robots for a variety of rewarding gratification they might receive when self-disclosing to robots and other artificial agents. One example is online users' willingness to self-disclose personal information to artificial agents like chatbots, and other online algorithms in online marketing and e-commerce settings (Moon, 2000), to receive personal recommendations (Laban & Araujo, 2020a, 2022). However, similarly to self-disclosures between humans (see Forgas, 2011; Ignatius & Kokkonen, 2012) people might also engage in self-disclosure with artificial agents and social robots due to social and emotional reasons and not only for economic reasons. There is a substantial body of literature using embodied and disembodied artificial agents for eliciting self-disclosure in a variety of settings, reporting that self-disclosing to artificial agents positively affects people's feelings and emotional well-being (see reviews and meta-analysis Bendig, Erb, Schulze-Thuesing, & Baumeister, 2019; Chattopadhyay, Ma, Sharifi, & Martyn-Nemeth, 2020; Hoermann, McCabe, Milne, & Calvo, 2017; Vaidyam, Wisniewski, Halamka, Kashavan, & Torous, 2019). For example, in a recent study, 115 participants shared emotional experiences with an artificial agent who provided either emotional or cognitive support messages. The results of the study entail that regardless of the type of support, self-disclosing emotions to the artificial agents fostered participants' emotional relief. After talking to the agents, participants felt better and expressed feeling closer to the agent and their desire to interact with it again (Pauw et al., 2022). Another study employed an emphatic disembodied conversational agent (i.e., a chatbot) to engage in verbal (text-based) interactions with 128 socially excluded participants, showing that interacting with the emphatic agent improved their mood (de Gennaro, Krumhuber, & Lucas, 2020).

Following the EASI model (Van Kleef, 2009; Van Kleef & Côté, 2022) that was mentioned earlier in this chapter, there are socio-emotional factors for which people would prioritize engagement in self-disclosure to artificial agents that extend from the positive affect experienced when engaging in self-disclosure. One such factor is *anonymity* and the lack of judgment in interactions with artificial agents. Anonymity is a substantial factor in this context as it is associated with increases in reporting disclosure in human-human self-disclosure (Clark-Gordon, Bowman, Goodboy, & Wright, 2019), specifically in disclosures about sensitive matters, like emotional well-being and mental health (McLay et al., 2008). Previous studies reported that people were more open to virtual agent interviewers than human interviewers in clinical interviews, demonstrating more willingness to disclose information about highly sensitive topics that can be associated with shame and stigma, or might just be considered sensitive (e.g., Lucas, Gratch, King, & Morency, 2014; Pickard, Roster, & Chen, 2016). For example, a study by Utami, Bickmore, Nikolopoulou, and Paasche-Orlow (2017) explored the reactions of older adults when having "end-of-life" conversations with a virtual agent. The study's results show that all study participants were comfortable discussing with the agent about death anxiety, last will and testament, providing compelling evidence for the potential utility of artificial agents in these complex socio-emotional domains. In a study by Lucas and colleagues (2014), participants (N = 239) were led to believe that the artificial agent was controlled by a human or by automation during mental health-related interviews. Participants who were led to believe that they were talking with an automated agent (compared to an agent operated by a human) reported lower fear of self-disclosure, lower impression management, displayed their sadness more intensely and were rated by observers as more willing to disclose. In another study, 203 students rated the sensitivity of different interview topics and indicated their preferences to disclose sensitive and personal information to a human or to an artificial agent. The study reports that there is a preference to disclose to an artificial agent when topics are more sensitive and are likely to evoke negative self-admissions. More specifically, participants stated that they would feel more comfortable discussing sensitive topics with an artificial agent because it could not judge them (Pickard et al., 2016). An additional study provided supporting evidence for it, showing that when engaging in mental health interviews, a sample of 55 students disclosed more sex-related symptoms to an artificial agent rather than to a real human expert (Yokotani, Takagi, & Wakashima, 2018). A recently conducted study with 22 participants further supports this with objective evidence and reports preliminary results stating that despite self-disclosing more (in terms of quantities) to an artificial agent that was introduced as a human (compared to an artificial agent that was introduced as a machine), the disclosures to the agent that was introduced as a machine were significantly more sentimental, and the agent was found to be perceived as friendlier (Warren-Smith, Laban, Marie-Pacheco, & Cross, 2023).

Nevertheless, beyond supporting the feeling of anonymity, artificial agents can build a sense of *rapport* by displaying (verbal and nonverbal) social cues of mutual liking, approval, attentiveness and coordination in their communication (Tickle-Degnen & Rosenthal, 1990) for engaging users in a more interactive dialogue (Gratch & Lucas, 2021). For example, another study by Lucas et al. (2017) employed a virtual agent that affords anonymity while building rapport to interview active-duty service members about their mental health symptoms when returning from a year-long deployment in Afghanistan. The study results show that participants disclosed more symptoms to a virtual agent interviewer than on the official Post-Deployment Health Assessment (PDHA), and then on an anonymized PDHA. The results of a larger sample experiment with active-duty and former service members reported a similar effect. Another early study by Bickmore, Gruber, and Picard (2005) showed in a longitudinal experiment with 33 young adults, that when the artificial agent showed more "relational" skills (behaviours that build and maintain good working relationships over multiple interactions like showing empathy, engaging in more social dialogue, and showing nonverbal immediacy behaviours) participants showed a significant increase in their will to communicate with the agent over time. Interestingly, even when using subtle cues to build rapport it seems to have a meaningful impact. A recent study with 40 participants shows that when artificial agents (voice assistants in this specific study, as the researchers used Amazon Alexa) are using subtle backchanneling cues (e.g., "aha", "go on", "ahm", "I see") it improves human users' perceived degree of active listening, and results in more emotional disclosure (i.e., participants using more positive words in their disclosures) (Cho, Motalebi, Sundar, & Abdullah, 2022).

Like other artificial agents (e.g., virtual humans, embodied and disembodied artificial agents), we have some (however, limited) empirical evidence for self-disclosures to social robots that follow similar principles. There are several studies addressing self-disclosure in child-robot interaction (e.g., Bethel, Stevenson, & Scassellati, 2011; Nijssen, Müller, Bosse, & Paulus, 2021), but since this thesis is focused on adults' interactions with social robots, I will not address these studies here. In terms of rapport, a study by Nakamura and Umemuro (2022) found that people might self-disclose more, and their self-esteem grows when self-disclosing to a robot that changes their listening attitude. This is also evidenced in people's perceptions of social robots' communication style in speech interactions, with participants (42 healthy adults) rating a robot that used a human-like communication style as more competent, warmer, and less discomforting, compared to robots employing machine-like communication style (Dautzenberg, Vos, Ladwig, & Von Der Putten, 2021). Moreover, a recent study suggests that rapport can also be experienced via disclosure reciprocity, as the study found that reciprocal self-disclosure from the robot increased liking in intimate self-disclosure. Nevertheless, the results of the study also report that reciprocal self-disclosure in non-intimate self-disclosure resulted in decreased rates of liking the robot (Mou, Zhang, Wu, Pan, & Ye, 2023). Similar evidence for the positive role of rapport is evidenced in a study by Duan, Yoon, Liang, and Hoorn (2021) showing that people in a more negative mood were more likely to benefit from self-disclosing to a robot compared to participating in a writing disclosure to a journal.

An extension to the study address also the gratification of anonymity when self-disclosing to robots, showing that self-disclosing to a robot was also more effective for those in a negative mood than self-disclosing on social media (Luo, Zhang, Chen, Hoorn, & Huang, 2022). Early work by Bartneck, Bleeker, Bun, Fens, and Riet (2010) shows that in a sample of 44 students, participants were less embarrassed when interacting with a "technical box" than with a social robot "iCat" (Phillips) in medical settings asking participants to undress and disclose relevant personal information (e.g., their weight). Interestingly, the lack of embodiment (of the technical box) made the participants feel less embarrassed in a vulnerable situation. In a recent study, 21 individuals with ASD were requested to answer 10 personal questions asked by three different agents – an android robot (a social robot with a realistic human appearance), a human interviewer, and a written passage on testing paper. The results of the study also highlight the positive role of anonymity in disclosures to social robots, with the android robot promoting more self-disclosure, especially about the negative topic compared to the human interviewer and the written passage (which also highlights the role of rapport) (Kumazaki et al., 2022). The role of anonymity is also present to a certain extent in a study by Neerincx, Edens, Broz, Li, and Neerincx (2022) with participants reporting to benefit the most from disclosing to the social robot Pepper (SoftBank) about their attitudes and opinions, compared to a number of other topics which are less sensitive or personal (e.g., work or study, tastes and interests). Another example of the role of anonymity when self-disclosing to robots is a study by Nomura and colleagues Nomura et al. (2020) that provides evidence for the benefits of employing social robots for minimising social tensions and anxieties. The study found that participants with higher social anxiety tended to feel less anxious and demonstrate lower tensions when knowing that they would interact with robots in opposition to humans in a service interaction. In addition, the study suggests that an interaction with a robot elicited lower tensions compared to an interaction with a human agent, regardless of one's level of social anxiety. In addition, the level of participant embarrassment in response to the android robot seemed to be lower compared to that in the human interviewer condition.

Like Nomura et al. Nomura et al. (2020) study, several other studies used self-disclosure with a social robot as a therapeutic activity. A study by Akiyoshi, Nakanishi, Ishiguro, Sumioka, and Shiomi (2021) employed the social robot Sota to perform a conversational stress-coping intervention aimed at encouraging participants (31 adults) to self-disclose to the robot about their worries. Accordingly, the robot was programmed to further ask about the problem presented by the participant to encourage them to self-reflect about it and provoke some emotional response. The study found that self-disclosing to the robot positively affected participants' moods and reduced their anger. Another study employed conversational-based cognitive behavioural therapy (CBT) using a social robot ("Rayen") for older adults (N = 4), meeting the robot twice a week for about an hour for four weeks. The results demonstrate that the individual subjects progressed through the sessions, their average sentence length increased, sharing more positive words, reporting for a more positive mood and some improvements in mental health symptoms. Overall, participants reported being satisfied with verbally interacting and self-disclosing to the robot (Dino, Zandie, Abdollahi, Schoeder, & Mahoor, 2019). It is important to consider that these results are limited due to the restrictive sample size and are mostly an indication of the usability of the developed system reported in the paper. A study by Birnbaum et al. (2016b) employed a non-humanoid social robot acting in a responsive way to human users' self-disclosures in two experiments. In the first experiment with 102 participants, they found that the robot's responsiveness increased the willingness to use it as a companion in stressful situations, and in the second experiment with 74 participants, they found that interacting with a responsive robot improved self-perceptions during a stress-generating task.

Interestingly, several studies report that the effects of self-disclosure are conditioned to different factors, like personalities, psychological tendencies, or emotional states. For example, one study with 81 participants found that participants with a higher tendency to anthropomorphise attributed higher levels of mind to the social robot Nao (SoftBank Robotics) in self-disclosure interactions (Eyssel, Wullenkord, & Nitsch, 2017). A cross-sectional study with 138 participants showed that there is a correlation between experiencing higher levels of loneliness due to the COVID-19 pandemic and showing a higher willingness to self-disclose to a robot (Penner & Eyssel, 2022). Another study with 80 participants reported a set of correlations between self-disclosure behaviour and personality traits, describing a positive correlation between interaction time and extraversion, a negative correlation between conscientiousness and interaction time, and a positive correlation between agreeableness and disclosure length (i.e., the number of words used per disclosure) (Neerincx et al., 2022).

In conclusion, people might prefer to engage in self-disclosure with social robots (as well as with other artificial agents) when experiencing social barriers like shame and stigma due to the perception of these interactions as more anonymous, perceiving the benefits of such exchange as a potential reward for their social behaviour. Moreover, it can be argued that anonymity is perceived as a gratification when choosing social robots and artificial agents as preferable media for self-disclosure as people experience higher degrees of anonymity during conversations with artificial agents, compared to conversations with humans (e.g., Lucas et al., 2014), and could afford to disclose more personal and sensitive matters (e.g., Pickard et al., 2016; Utami, Bickmore, Nikolopoulou, & Paasche-Orlow, 2017; Yokotani et al., 2018). Due to the tendency to associate acts of interpersonal communication like self-disclosure (Jourard, 1971) with social behaviour (Berger, 2005), people are more likely to self-disclose and engage in richer self-disclosures to agents that demonstrate richer social cues and build rapport (e.g., Cho et al., 2022; Nakamura & Umemuro, 2022). This act adheres to the expected reciprocity which would follow typical interactions of self-disclosure (Archer & Berg, 1978; Becker, 1986; Derlega et al., 1973). Hence, self-disclosure to social robots requires a delicate balance between simulating the feeling of anonymity while demonstrating cues of rapport. In other words, people would like to engage in self-disclosure to social robots when feeling like they are disclosing to an interactive social entity, receiving social confirmation for their social behaviour (i.e., sustaining high levels of rapport), while objectively knowing that this social entity is an object lacking human judgment offering minimal social consequences (e.g., shame and stigma) when self-disclosing personal and sensitive matters (i.e., sustaining the feeling of staying anonymous). Finally, these self-disclosure interactions have the potential to support people's emotional well-being, simulating positive affect and offering therapeutic opportunities.

1.7 Operationalization, manipulation, and measurement of self-disclosure

Eliciting self-disclosure in experimental and controlled settings is not an easy task (Chittick & Himelstein, 1967), considering that self-disclosure is a dynamic social behaviour that is aimed at establishing relationships between closed individuals, rather than with strangers (Aron, Melinat, Aron, Vallone, & Bator, 1997), let alone with social robots (Martelaro, Nneji, Ju, & Hinds, 2016). The experimental techniques of studying self-disclosure have been widely influenced by *elicitation techniques* of psychotherapy (Berg & Derlega, 1987), where a practitioner aims to encourage patients to reveal their thoughts, emotions and needs (Farber, 2006; Stiles, 1995). An additional influence can be drawn from the medical practice of health data acquisition, where medical doctors try to elicit relevant information from patients to identify symptoms (Naldemirci et al., 2020; Senteio & Yoon, 2020; Singh Ospina et al., 2019). The development of elicitation tasks and behavioural paradigms aimed at eliciting self-disclosure in experimental studies is a complex and multi-faceted process that considers several key considerations (Chittick & Himelstein, 1967; Prior, Mather, Ford, Bywaters, & Campbell, 2020). Theoretically, the design of these tasks and paradigms is guided by existing models of self-disclosure behaviour that aim to manipulate the *orientation* (i.e., the entity to which the disclosure is oriented and the social dynamic; Earle, Giuliano, & Archer, 1983) and the *function* (i.e., that activity to which self-disclosure is used; Derlega & Grzelak, 1979) of self-disclosure (Archer, 1987), to further understand the psychological processes that influence self-disclosure, such as motivation, social norms, intimacy, and trust (Chaudoir & Fisher, 2010; Ignatius & Kokkonen, 2012). Practically, the development of these tasks must consider factors such as feasibility, cost and resource requirements, and ethical and privacy considerations (M. Lee et al., 2022). Empirically, researchers use prior research findings, pilot studies, qualitative data, and observational data to inform the design of elicitation tasks and paradigms and to ensure that they effectively elicit self-disclosure behaviour in a controlled environment (Chittick & Himelstein, 1967; Cooke, 1994).

In the study of self-disclosure in interpersonal settings, several behavioural paradigms and experimental tasks are commonly used to elicit and manipulate self-disclosure. *Interview-based techniques* involve participants revealing personal information in a controlled, step-by-step manner to examine the effects of increasing levels of self-disclosure on interpersonal interactions (e.g., Janofsky, 1971; Pickard, Wilson, & Roster, 2018). This is a meaningful method in the experimental study of self-disclosure, as it puts the individual at the centre of the paradigm, creating ideal settings for self-disclosure and sharing personal and even sensitive matters (Chittick & Himelstein, 1967; Prior et al., 2020; Vondracek, 1969). *Self-introduction* and *self-presentation paradigms* can elicit self-disclosures from individuals when requested to present themselves, to another individual, a group, or via media (Chittick & Himelstein, 1967; Himelstein & Kimbrough, 1963). This technique also allows situating the subject in the centre of the paradigm, encouraging personal disclosures, while simulating additional psychological dimensions, like the mood of the subject (e.g., simulating stress from public speaking) or the context of the disclosure (situating the disclosure in common self-disclosure conditions where one presents themselves and establish new relationships). Nevertheless, the paradigm is more restrictive when trying to control the experimental environment, often requiring field studies (e.g., Himelstein & Kimbrough, 1963) and often yielding large variances in the subject's behaviour due to personality differences when encountering self-presentation manipulations (Chittick & Himelstein, 1967). *Reciprocal disclosure paradigms* explore mutual self-disclosure through the exchange of personal information between participants (e.g., Sprecher & Treger, 2015) and can be beneficial when studying both interchangeable roles of sender and receiver while providing an ecological experience. However, the variance between interactions might be a confound in the experimental design. Employing *interpersonal interaction paradigms* simulates self-disclosure during a conversation with a confederate who is following a scripted procedure or clear instructions (e.g., merely listening or asking specific questions throughout a flowing dialogue) as a sort of role-playing (e.g., Sprecher, Treger, & Wondra, 2013). Like using interview-based techniques, here the subject is also at the centre of the interaction while simulating a more ecological experience by using a confederate that is showing cues of rapport to enhance the interaction's engagement, like the reciprocal disclosure paradigms. Differently from reciprocal disclosure paradigms, here the confederate is following a clear procedure to reduce the potential for confounding effects and sustain a more systematic experimental design. These paradigms and tasks complement each other in providing a comprehensive understanding of self-disclosure in interpersonal settings, simulating the behaviour of self-disclosure via providing clear instructions and addressing the content of the interactions to personal matters like factors related to one's quality of life or meaningful life events (Aron et al., 1997).

Self-disclosure has been studied and conceptualized in the psychological literature in many ways and has been assessed using different instruments that measure its different dimensions. Single dimensions cannot capture the complex nature of self-disclosure, as it is a multidimensional behaviour (Kreiner & Levi-Belz, 2019); perceptions of self-disclosure can be subjectively reported and objectively observed differently from behaviour and content (Levi-Belz & Kreiner, 2016). *Self-reported measures* involve participants completing questionnaires or interviews that ask about their self-disclosure behaviour, in general, within a specific task (i.e., during an experimental task), or retrospectively (Kreiner & Levi-Belz, 2019). Common tools for self-report measures include the *Jourard Self-Disclosure Questionnaire* (Jourard, 1971) and *Distress Disclosure Index* (Kahn & Hessling, 2001) that were employed in this thesis (see other tools at Kreiner & Levi-Belz, 2019). This method is practical as it is easy to administer and provides a subjective perspective on self-disclosure. However, it may be subject to bias, as participants may not accurately report their behaviour. *Observer ratings* involve independent observers rating the level and type of self-disclosure displayed by participants (e.g., Levi-Belz & Kreiner, 2016). This method provides a more objective assessment of self-disclosure and can be more comprehensive than self-report measures. However, observer ratings may be subject to observer bias and may not capture the nuanced aspects of self-disclosure behaviour. Moreover, it requires substantial amounts of data for achieving reliable measurements via inter-rater reliability (see Villanueva & Johnson, 2011).

Content analysis involves the examination of the specific topics and themes that participants disclose about. This method can be conducted manually or using computational tools such as the *Linguistic Inquiry and Word Count* software (i.e., LIWC; Tausczik & Pennebaker, 2010). Content analysis provides a detailed analysis of self-disclosure behaviour and aligns with the view of self-disclosure as a form of communication. Similarly to observer ratings, *manual content analysis* can be time-consuming, but may capture complex and latent concepts in people's disclosures (e.g., levels of intimacy) (e.g., L. Chen, Hu, Shu, & Chen, 2019). *Computational automated content analysis* uses algorithms to analyse large amounts of data, including self-disclosure behaviour and can provide a more efficient analysis of self-disclosure. Automated techniques can provide values for *disclosure quantities* (i.e., the volume of shared content; e.g., disclosure duration in seconds, and length in number of words). Self-disclosure has been linked to the total number of words a person produces during an interaction or within a single turn in the interaction. Higher word counts are associated with greater self-disclosure (Barak & Gluck-Ofri, 2007; Joinson, 2001; Pedersen & Breglio, 1968). Another approachable computational method is *sentiment analysis* (e.g., VADER, see Hutto & Gilbert, 2014), a natural language processing method which extracts and analyses information classifying and rating positive and negative keywords (e.g., Baroutsou et al., 2023; Keijsers, Bartneck, & Kazmi, 2019). These measures provide valuable insights into different aspects of self-disclosure in interpersonal interactions. However, automated methods may not capture the full context and emotional aspects of self-disclosure behaviour and may be limited by the specific algorithms used. The advancement of *acoustic analysis* methods has enabled researchers to study speech acoustics and link them to the psychological processes involved in verbal communication. The physical analysis of vocal characteristics in spoken communication is a recent approach to measuring participants' in-person experiences and has been widely studied in emotion research (Scherer, Johnstone, & Klasmeyer, 2003). *Vocal prosody features* and voice signals like vocal pitch, intensity, energy, and harmonicity provide implicit indicators of behaviour and emotions conveyed and expressed in self-disclosure (Frick, 1985; Roach, Stibbard, Osborne, Arnfield, & Setter, 1998; Scherer et al., 2003; Y. Yang, Fairbairn, & Cohn, 2013), and the psychophysiological underpinnings that associate with these (e.g., Giddens, Barron, Byrd-Craven, Clark, & Winter, 2013; Ruiz, Legros, & Guell, 1990; Slavich, Taylor, & Picard, 2019; van Puyvelde, Neyt, McGlone, & Pattyn, 2018; Y. Yang et al., 2013). Nevertheless, while these measurements can provide meaningful evidence for the speaker's emotional state and bodily experience during self-disclosure, they cannot provide additional information regarding the depth and breadth of it.

Finally, qualitative methods, such as *in-depth interviews*, *observations*, and *focus groups*, can provide a rich and nuanced understanding of self-disclosure behaviour, including the context and emotions involved, and allows researchers to practice induction and theory building (e.g., Klim et al., 2021; Pluta, 2021). Common tools for qualitative methods include *semi-structured interviews*, focus groups, and *thematic analysis*. However, this method may be subject to researcher bias and may not provide a comprehensive analysis of objective self-disclosure behaviour. Moreover, qualitative evaluation is time-consuming, requires specialized interpretation, and accordingly, it allows the researcher to analyse only a limited number of cases, drastically impacting the generalizability of study results. Each of these measurement methods has its own strengths and limitations, and the choice of method will depend on the specific research question and paradigm being used. The use of multiple methods can provide a more comprehensive and nuanced understanding of self-disclosure via its multidimensional lens.

1.8 Current behavioural paradigm

In HRI research, self-disclosure tasks aim to elicit self-disclosure behaviour from participants in interaction with a robot. These tasks can involve participants engaging in conversation or providing personal information to the robot, however, the use of these methods in HRI research may face specific challenges, such as the limited expressive capabilities of robots and the difficulty in capturing the full context and emotions involved in self-disclosure behaviour in HRIs. The use of robots in self-disclosure tasks can provide a unique opportunity to study self-disclosure behaviour in a controlled and standardized environment. Nevertheless, the use of robots in self-disclosure tasks may also raise ethical and privacy concerns (see M. Lee et al., 2022), as participants may not fully understand the extent of their self-disclosure behaviour and the potential use of their personal information. In terms of measurements, the use of robots may also introduce the need to measure additional dimensions of self-disclosure and associated parameters, such as the level of comfort in disclosing information to a robot, and attributed degrees of mind to the robot. The use of multiple methods and careful consideration of the specific challenges and limitations of each method can provide a more comprehensive and nuanced understanding of self-disclosure behaviour in HRI research. The use of task-specific measures and the examination of self-disclosure behaviour in different interaction contexts can also provide a deeper understanding of the complex nature of self-disclosure in human-robot interaction.

Previous studies that investigated relationship formation and disclosure with artificial agents followed conceptual frameworks for inducing rich disclosures and forming meaningful connections (e.g., Croes & Antheunis, 2020, 2021; Riddoch & Cross, 2021). For example, a study by Croes and Antheunis (2021) presented an implementation of 36 questions as a method to generate interpersonal closeness ("36 questions to love"; Aron et al., 1997) and elicit self-disclosure from human users to a chatbot. Due to the technical limitations of employing social robots in open conversations and reciprocal interactions, the self-disclosure elicitation task for the studies presented in this thesis was designed using an interview-based technique while employing principles of the interpersonal interaction paradigm. In each of the empirical studies presented, the robots and conversational agents were operated using the *Wizard-of-Oz* (WoZ) technique. This is an experimental method where an agent is controlled by a human operator (see Riek, 2012). In this approach, the robot or artificial agent asked participants a varying number of questions, depending on the specific experimental design employed in each chapter of this thesis. The purpose of these questions was to elicit rich disclosures. In accordance with Leite et al. (2013) guidelines for experimental designs with social robots in long-term interactions, the interactions followed a clear structure and routine, including greetings and farewells, and demonstrating appropriate affective and emphatic responses to participants' answers to provide a sense of personal interactions and encourage self-disclosure (see Leite et al., 2013). By following a clear script and protocol the robot acted like a trained confederate in an interpersonal interaction paradigm, eliciting self-disclosure from the participant while demonstrating the necessary social cues for demonstrating rapport. By positioning the robot as an interviewer, the task ensured that participants would have the stage to self-disclose rather than engage in other forms of social communication like small talk or general information exchange. Participants were not aware of the deception until they finished their participation in the studies.

The content of each task was also designed to ensure self-disclosure. The questions and topics in the tasks designed for this thesis were influenced by the topics of disclosure presented in Jourard Self Disclosure Questionnaire (Jourard, 1971) and Connell et al. (2012) framework that includes six domains of quality of life that are crucial for positive mental health within emotional well-being (see also Connell, O'Cathain, & Brazier, 2014). I conceptualized questions about topics relating to everyday experiences (i.e., work-life balance and finances, social life and relationships, and health and well-being) that can elicit meaningful disclosures when communicated by a social robot. The topics in the developed tasks are intended to capture participants' disclosures regarding everyday topics and matters that people often discuss, sharing non-sensitive information that is suitable for HRI experiments, while also touching more personal matters depending on the context of the interaction (see Kreiner & Levi-Belz, 2019). The framework by Connell et al. (2012) introduces guidelines via six main themes for asking questions that capture and elicit disclosures that relate to different elements of quality of life within counselling psychology settings and mental health therapy. The guidelines and themes were defined by Connell et al. (2012) after reviewing and synthesizing qualitative research studies (especially from the counselling psychology literature, psychotherapy, and mental health therapy literature) that explicitly asked adult participants with mental health problems about the factors they considered important to their quality of life or how it had been impacted by their mental health. Based on Connell et al. (2012) review results the six themes are: (1) *Well-being* and *Ill-being*, (2) *Control*, *Autonomy*, and *Choice*, (3) *Self-Perception*, (4) *Belonging*, (5) *Activity*, (6) *Hope* and *Hopelessness*. Hence, the self-disclosure tasks designed for this thesis were aimed at eliciting meaningful disclosures while also initiating self-reflection (see Creswell et al., 2007; Tamir & Mitchell, 2012) and capturing meaningful information regarding one's quality of life and mental health, following Connell et al. (2012) framework (2012). The phrasing of each question under each topic followed Aron et al. (1997) approach for questions and practical methodology for creating interpersonal closeness in an experimental context.

1.9 Current dissertation

Following this Introduction chapter, this thesis includes three empirical chapters describing laboratory and field experiments investigating the underlying psychological mechanisms of perception and behaviour within human-robot communication, and their potential deployment as interventions for emotional well-being.

People infer a great deal about what an agent does or can do, based on its embodiment (i.e., what it looks like, how it moves, etc.; Anderson, 2003; Hortensius et al., 2018; Wallkötter, Tulli, Castellano, Paiva, & Chetouani, 2021). However, it remains unclear how self-disclosures to artificial agents differ depending on the agent's embodiment. Embodied social cues can facilitate self-disclosures to artificial agents via building rapport (Gratch & Lucas, 2021), but it can also be perceived as the display of emotional expression (Hortensius et al., 2018; Laban, Le Maguer, et al., 2022) that can trigger certain emotions (see Van Kleef, 2009; Van Kleef & Côté, 2022) and hamper self-disclosure behaviour. Accordingly, the goal of Chapter 2, the first empirical chapter (see Laban, George, Morrison, & Cross, 2021) of this project, was to explore how a social robot's embodiment influences people's disclosures in measurable terms, and how these disclosures differ from disclosures made to humans and disembodied agents. Hence, the first research question (RQ1) in my project is *to what extent disclosures to social robots differ from disclosures to humans and disembodied agents?*

An additional challenge in HRI research is replicating and extending lab-based findings to better understand how short, constrained laboratory manipulations might translate to real-world scenarios (Cross & Ramsey, 2021; Gunes et al., 2022; Henschel, Hortensius, & Cross, 2020; Henschel et al., 2021; Irfan et al., 2018). Since interactions with social robots are novel and exciting for many people, one particular concern in this specific area of HRI is the extent to which behavioural and emotional expressions might develop from initial interactions with a robot, when its novelty is particularly salient, to responses and behaviours that are sustained over time (Smedegaard, 2019, 2022). This challenge is noticeable in social interactions designed to support people's emotional well-being, with limited evidence for how social robots can support people's emotional well-being over time via self-disclosure. Moreover, self-disclosure interactions with social robots rarely extend from one single interaction, and accordingly, we have limited knowledge of how this process, which is so valuable in human-human relationship formation (see Altman & Taylor, 1973), affects long-term relationship establishment with social robots. This includes the way people perceive and behave towards the robot, and how these interactions make people feel. Accordingly, the goal of Chapter 3, the second empirical chapter (see Laban, Kappas, Morrison, & Cross, 2022a) of this project was to study how prolonged and intensive long-term interactions with a social robot affect people's self-disclosure behaviour towards the robot, perceptions of the robot, and how it affected factors related to well-being. Hence, the second research question (RQ2a) is *to what extent people's self-disclosures, perceptions of the robot, as well as well-being, are affected over time in long-term interactions with a social robot?* In addition, to have a further understanding of the application of social robots in different emotional settings and their varying abilities to simulate affect via conversation, the role of the interaction's discussion theme was also examined. Hence, in Chapter 3, I was also asking the following research question (RQ2b) - *To what extent people's self-disclosures, perceptions of the robot, as well* *as well-being, are affected due to the discussion theme in long-term interactions with a social robot?*

The last challenge I aspired to address through this thesis related to the implementation of a social robot as a mental health intervention. More specifically, with a unique target group that is living with considerably difficult life situations and could use the support of a social robot intervention for their emotional well-being. Emotional distress is an unpleasant emotional state that occurs when one is limited or unable to adapt to stressors and their consequences, perceived and actual (Ridner, 2004). Considering the vast benefits of using self-disclosure as a technique to interpersonally regulate emotions and cope with emotional distress (Coan, 2012; Zaki & Williams, 2013), the goal of Chapter 4, the final empirical chapter (see Laban, Morrison, Kappas, & Cross, 2023) of this project was to test a long-term and intensive social robot intervention with people that are living with considerably difficult life situations, to have a better understanding of how this sort of interaction can support them. For the context of this study - these were informal caregivers. Informal caregivers often struggle in managing to cope with both the stress and the practical demands of the caregiving situation (Pearlin, Mullan, Semple, & Skaff, 1990; Hiel et al., 2015; Collins & Kishita, 2020b; Gérain & Zech, 2019). Given the importance of self-disclosure for psychological health, and how it could support informal caregivers coping with emotional distress, here I aimed to investigate the potential of employing a social robot for eliciting self-disclosure among informal caregivers over time, supporting their emotional well-being and implicitly encouraging them to adapt emotion regulation skills. Hence, the last research question (RQ3) for this project is *To what extent does self-disclosing to a social robot across several sessions over the course of 5 weeks impact informal caregivers' self-disclosure behaviour toward the robot, perceptions of the robot, and their emotional well being and emotion regulation?*

In the final discussion chapter (Chapter 5), I summarise the current findings and discuss the contributions, implications and limitations of my work. I reflect on the contribution and challenges of this research approach along with the provision of some future directions for researchers in the relevant fields.

Chapter 2

Tell Me More! Assessing Interactions with Social Robots From Speech

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A preliminary version of this chapter was accepted for publication and presentation at *ACM International Conference on Human–Robot Interaction 2020* under the title: "Let's Talk About It! Subjective and Objective Disclosures to Social Robots" (see Laban, Morrison, & Cross, 2020), and a full version of this chapter was accepted for publication in *Paladyn, Journal of Behavioral Robotics* on 09/10/2020 (see Laban, George, et al., 2021).

Abstract

As social robots are increasingly introduced into health interventions, one potential area where they might prove valuable is in supporting people's psychological health through conversation. Given the importance of self-disclosure for psychological health, this study assessed the viability of using social robots for eliciting rich disclosures that identify needs and emotional states in human interaction partners. Three within-subjects experiments were conducted with participants interacting with another person, a humanoid social robot, and a disembodied conversational agent (voice assistant). We performed a number of objective evaluations of disclosures to these three agents via speech content and voice analyses, and also probed participants' subjective evaluations of their disclosures to the three agents. Our findings suggest that participants overall disclose more to humans than artificial agents, that agents' embodiment influences disclosure quantity and quality, and that people are generally aware of differences in their personal disclosures to the three agents studied here. Together, the findings set the stage for further investigation into the psychological underpinnings of self-disclosures to artificial agents and their potential role in eliciting disclosures as part of mental and physical health interventions.

2.1 Introduction

People tend to disclose thoughts and feelings with others, especially when experiencing unique and challenging life events (Gable et al., 2004). Disclosure thus serves an evolutionary function of strengthening interpersonal relationships, but also produces a wide variety of health benefits, including helping people to cope with stress and traumatic events and to elicit help and support (Frattaroli, 2006; Frisina et al., 2004; Kennedy-Moore & Watson, 2001). Moreover, self-disclosure appears to play a critical role in successful health treatment outcomes (Sloan, 2010) and has a positive impact on mental and physical health (Derlega et al., 1993). Given the importance of self-disclosure for psychological health, here we are interested in assessing the viability of using social robots for eliciting rich disclosures to identify people's needs and emotional states.

Social robots, defined here as autonomous machines that interact and communicate with humans or other agents by following social behaviours and rules (Breazeal, 2003), are gradually being introduced in psychosocial health interventions (see N. L. Robinson et al., 2019) as well as in mental health and well-being research (see Scoglio et al., 2019). Concurrently, social robot-based interventions are also being introduced into care settings, tasked with providing physical assistance (e.g., Broadbent et al., 2014, 2012; Akalin, Kristoffersson, & Loutfi, 2019; Akalin, Kiselev, Kristoffersson, & Loutfi, 2018; Feingold-Polak et al., 2018; Polak & Tzedek, 2020), serving as companions, providing emotional support, and contributing to the mental well-being of patients (e.g., Broadbent, 2017; Jeong et al., 2015; N. L. Robinson et al., 2019; Ostrowski, DiPaola, Partridge, Park, & Breazeal, 2019; H. Robinson et al., 2013; Scoglio et al., 2019; Ling & Björling, 2020; Yu et al., 2015). Autonomous systems such as social robots can support care recipients in a variety of ways, but can also support their caregivers' physical and mental health (see Petrovic & Gaggioli, 2020). Moreover, social robots are increasingly being built equipped with technologies (e.g., sensors, cameras, and recorders) that promote high fidelity data collection and on-line, on-going analysis of a human interaction partner's behaviour. When implemented in an ethical and responsible manner, such features hold promise for robots being able to analyse and respond to user responses during an interaction in a sensitive, timely and nuanced manner.

In order for health interventions to succeed, they depend on open channels of communication where individuals can disclose needs and emotions, from which a listener can identify stressors and respond accordingly (Colquhoun et al., 2017; Wight et al., 2016). This is particularly important for self-help autonomous systems, and for personalizing interventions and other assistive solutions, as these should be able to use the rich input provided by human users to extract salient information, identify patterns and emotional states, and respond accordingly (Riva, Baños, Botella, Wiederhold, & Gaggioli, 2012). It follows from this that socially assistive robots should also be attuned to the content and emotion of disclosed information. While social robots and other artificial agents do not (yet) offer the same opportunities as humans for social interactions (Cross, Hortensius, & Wykowska, 2019), their cognitive architectures and embodied cognition can nonetheless elicit socially meaningful behaviours from humans (see Beck, Yumak, & Magnenat-Thalmann, 2017a; Hortensius et al., 2018; Sandini, Mohan, Sciutti, & Morasso, 2018). Accordingly, people infer a great deal about what an agent does or is capable of doing, based on its embodiment (i.e., what it looks like, its physical presence, how it moves, etc.). In addition, other cues of embodiment are driven by a human interaction partner's cognitive reconstruction (Hortensius & Cross, 2018), wherein their beliefs or expectations about an agent further shape perception and behaviour (Cross, Ramsey, Liepelt, Prinz, & Hamilton, 2016; Klapper, Ramsey, Wigboldus, & Cross, 2014; Laban & Araujo, 2020b; Özdem et al., 2017).

However, a number of outstanding questions remain regarding the utility and scope of using social robots in self disclosure settings, which require careful evaluation before such agents might be deployed in actual care contexts. For instance, it remains unclear the extent to which individuals convey emotions and personal information in disclosures to social robots, as well as how disclosures to artificial agents differ depending on the agent's embodiment or physical presence. As socially assistive robots continue to be developed with the aim to provide meaningful support to people across a variety of contexts, our goal with this study was to explore how a social robot's embodiment influences people's disclosures in measurable terms, and how these disclosures differ from disclosures made to humans and disembodied agents. Hence, our primary research question concerns the extent to which disclosures to social robots differ from disclosures to humans and disembodied agents.

2.1.1 Embodiment as a social cue

The media richness theory (MRT; Daft & Lengel, 1986) explains that a communication medium's ability to reproduce information sent through it is driven by its ability to communicate a complex message adequately. Hence, personal communication behaviours, such as disclosure, would typically be transmitted better (or with greater fidelity) through media with the capacity to convey richer social cues, like gestures and body language (Carlson & Zmud, 1999; Daft & Lengel, 1986). However, MRT was originally concerned with computer-mediated communication (CMC), and accordingly, social cues within the MRT framework are bound to human origins. In this study, we address this in the context of HRI, and explore people's disclosures as a reaction to agents' physical features, when these are the only available cues to an agent's intentions. Therefore, we ask whether an agent's embodiment influences people's disclosures to them, in terms of both objective and subjective measurements of disclosure quality.

Within the MRT framework (Daft & Lengel, 1986), the complexity of a communication message is related to the task and the context of the interaction, but not the content of the interaction. Carlson and Zmud (1999) expanded on this and explained that the topic of the interaction also has a substantial impact on how one experience the interaction, and accordingly, respond and communicate. Therefore, we are also asking how disclosures differ in relation to the agent's embodiment in comparison to the disclosure topic.

2.1.2 Subjective and objective disclosure

Self-disclosure has been studied and conceptualized in the psychological literature in many ways and has been assessed using different instruments that measure its different dimensions (Kreiner & Levi-Belz, 2019). Self-reported measurements (e.g., Jourard, 1971; Jourard & Lasakow, 1958) convey subjective dimensions of self-disclosure evaluating people's retrospective perceptions (Kahn, Hucke, Bradley, Glinski, & Malak, 2012; Kreiner & Levi-Belz, 2019), whereas objective dimensions of disclosure include depth, breadth, and volume of a disclosure (Antaki, Barnes, & Leudar, 2005; Omarzu, 2000) from verbal output (Kreiner & Levi-Belz, 2019; Tausczik & Pennebaker, 2010; Weiss, 2019). Moreover, vocal prosody features and voice signals provide implicit indicators to behaviour and emotions (Frick, 1985; Roach et al., 1998; Y. Yang et al., 2013; Scherer et al., 2003), and the psycho-physiological underpinnings that associates with these (e.g., Giddens et al., 2013; Ruiz et al., 1990; Slavich et al., 2019; van Puyvelde et al., 2018; Y. Yang et al., 2013). Single dimensions cannot capture the complex nature of self disclosure, as it is a multidimensional behaviour (Kreiner & Levi-Belz, 2019); perceptions of self-disclosure can be objectively observed differently from behaviour and content (Levi-Belz & Kreiner, 2016). Several HRI studies have addressed artificial agents influence on disclosure (see Aroyo, Rea, Sandini, & Sciutti, 2018; De Groot, Barakova, Lourens, van Wingerden, & Sterkenburg, 2019; Kumazaki, Warren, et al., 2018; Laban & Araujo, 2020a; Birnbaum et al., 2016b, 2016a; Hoffman, Birnbaum, Vanunu, Sass, & Reis, 2014; Björling, Rose, Davidson, Ren, & Wong, 2019; Traeger, Sebo, Jung, Scassellati, & Christakis, 2020; Ho, Hancock, & Miner, 2018; Johanson et al., 2019, 2020; Kumazaki, Yoshikawa, et al., 2018; Y.-C. Lee, Yamashita, Huang, & Fu, 2020; Ling & Björling, 2020; Shiomi et al., 2020; Lucas et al., 2014, 2017), however, evidence is limited regarding how people's subjective perceptions of self-disclosure aligns with objective measures of self-disclosure. Here we evaluate both people's perceptions and their actual disclosures across three experiments.

2.1.3 Current study

In our study, we are primarily interested in the extent to which disclosures to social robots differ from disclosures to humans and disembodied conversational agents. Furthermore, we investigate how disclosures differ in relation to the agent's embodiment in comparison to the disclosure topic. We wish to explore and describe differences in subjective and objective disclosures to social robots and how people's perceptions and their actual disclosures are related across three experiments. Disclosure is important in order for a person to benefit fully from an automated assistant, which should be able to recognize commands and tasks, as well as respond appropriately to a human user's needs, emotions, and psychological state.

We conducted three laboratory experiments to address research questions centred on this topic. Experiment 1 was designed to provide an initial indication and baseline results regarding subjective and objective disclosures to social robots (see Laban, Morrison, & Cross, 2020). The sample of the study included student participants. Experiment 2 replicated the design of Experiment 1 with a sample of native English speakers only. For this experiment, each interaction involved two questions to enhance the depth of communication between the participants and the three agents. In Experiment 3, we replicated the experimental design again, this time with a larger sample size for greater statistical power, which enabled us to further probe the reliability and generalizability of the findings from the first two experiments. Furthermore, based on the findings of the two preceding experiments, the sequencing of the questionnaires was modified to guarantee that participants accurately recollect the pertinent information while responding to them.

2.2 Method

Consistent with recent proposals (Nelson, Simmons, & Simonsohn, 2012; Simmons, Nelson, & Simonsohn, 2011), we report how we determined our sample size, all data exclusions, all manipulations and all measures in the study. In addition, following open science initiatives (e.g., Munafò et al., 2017), the de- identified data sets, stimuli and analysis code associated with this study are freely available online (see Laban, George, Morrison, & Cross, 2020)[1]. By making the data available, we

[1] osf.io/f3d5b

enable and encourage others to pursue tests of alternative hypotheses, as well as more exploratory analyses.

In order to address our primary research questions, 3 laboratory experiments were conducted. Preliminary results of the first experiment were reported as late breaking reports in the Human-Robot Interaction conference (HRI) 2020 (see Laban, Morrison, & Cross, 2020).

2.2.1 Population

Experiment 1

The first experiment consisted of 26 university students between the ages of 17 and 42 years old ($M = 24.42, SD = 6.40$) including 61.5 % females. Participants reported being from different national backgrounds, with 50% of participants reporting English as their native language. For most participants (88.50 %), this was their first interaction with a robot. All participants were recruited using the University of Glasgow's participant pool. Participants provided written informed consent before taking part in any study procedures and were compensated for their time with either course credits or cash (£3 for 30 minutes of participation). All study procedures were approved by the research ethics committee of the University of Glasgow.

Experiment 2

Following the first experiment, the target population of the second experiment was limited to native English speakers. This was highlighted in the advert that was shared over email to potential participants, on the advert in the University of Glasgow's subjects-pool, and only potential participants that were defined as native English speakers in the subjects-pool system could sign-up to participate in the study. Participants from the previous experiment (Experiment 1) were excluded from participating in Experiment 2.

The participant sample for Experiment 2 consisted of 27 participants between the ages of 20 to 62 years old ($M = 28.60, SD = 9.61$) including 59.30 % females. All of the participants reported English as their native language, whereas 85.20 % of the participants reported being from the United Kingdom, 11.10 % reported being from other English speaking countries, and 3.70 % (one participant) reported being from Chile. For most of the participants (81.50 %) this was their first interaction with a robot. The participants were recruited using The University of Glasgow's subjects-pool or by being directly contacted by the researchers. All of the participants provided written informed consent before taking part in any study procedures and participants were compensated for their time with either credits or with cash (3£ - rate of 6£ for one hour). All study procedures were approved by the research ethics committee of the University of Glasgow.

Experiment 3

Following the first and second experiments, the target population of the third experiment was limited to native English speakers. This was highlighted in the adverts shared over email to potential participants and on the University of Glasgow's subject pool, and only native English speakers in the subject pool system could sign up to participate in the study. Participants from Experiments 1 and 2 were excluded from participating in Experiment 3.

The study consisted of 65 participants, of which 4 were excluded due to technical failures. The 61 participants were between the ages of 18 to 43 years old ($M = 23.02, SD = 4.88$) including 67.20% females. All of the participants reported English as their native language, whereas 63.70% of the participants reported being from the United Kingdom, 16.30% reported being from other English speaking countries, and 19.5% reported being from non-English speaking countries. For most of the participants (72.10%) this was their first interaction with a robot. The participants were recruited using The University of Glasgow's subjects-pool or by being directly contacted by the researchers. All of the participants provided written informed consent before taking part in any study procedures and participants were compensated for their time with either credits or with cash (3£ - rate of 6£ for one hour). All study procedures were approved by a research ethics committee of the University of Glasgow.

2.2.2 Design

The three laboratory experiments consisted of within-subjects experimental designs with three treatments, applying a round-robin test. In a randomized order, all participants interacted with 3 agents: (1) a humanoid social robot, (2) a human agent, and (3) a disembodied agent (voice assistant).

In Experiment 1, participants were asked one question from each agent about one of the three topics that were relevant to a student's experience (see section 2.2.6). Based on our experience and observations from running Experiment 1, as well as qualitative feedback received from participants, we decided to update and improve some aspects of our experimental approach when running Experiment 2. As our participant sample was not limited to students in Experiment 2 (see section 2.2.6) and Experiment 3 (see section 2.2.6), participants were asked two questions by each agent about one of three more general topics. In Experiment 2, the topics surveyed the same ideas as Experiment 1, but were not constrained to the context of student experience. Based on our observations and participants feedback from Experiment 2, we designed Experiment 3 to collect data from a larger sample size. To optimize disclosure and ensure the data collected could extend the results of the previous experiments, we streamlined our questions so that multiple questions that were similar were combined into a single question.

The rationale behind the slight variations present across the 3 experiments that compose the present study was to (a) improve the experimental design (i.e., ask more questions) following each experiment; (b) adapt questions based on participants' feedback, our observations, and the participant sample being recruited; and (c) provide evidence that even though the exact content of the questions changed across experiments, the effect of embodiment on key factors of self-disclosure endured compared to the effects of the topics of the disclosure.

2.2.3 Stimuli

The three agents communicated the same questions using different visual and verbal cues that corresponded appropriately to their form and capabilities.The same experimenter (GL) operated the Wizard of Oz (WoZ) of both devices (the humanoid social robot and the disembodied agent) via dedicated software, and also served as the human agent for all three experiments. The questions were pre-scripted and integrated into the WoZ systems to minimize any possibility of mistakes and errors. Each agent asked each question equally across all three experiments, as per random assignment.

Humanoid Social Robot

This treatment condition used the robot NAO (Softbank Robotics), a human-like social robot that can communicate with humans via speech and can also be programmed to display appropriate gaze and body gesture cues to increase its appearance of "socialness" (see Figure 2.1). NAO communicated with participants in this study via the WoZ technique controlled by the experimenter via a PC laptop. All of the pre-scripted questions and speech items were written and coded in the WoZ system, with the experimenter (GL) controlling NAO by pressing buttons on a PC laptop. Accordingly, the procedure followed clear pre-programmed protocol where the experimenter did not need to speak or type anything during the interaction but only press a button to start the interaction.

In the first and second experiments, when participants were answering NAO's questions, NAO directed its gaze toward the participant and engaged in simulated breathing to contribute to its human-like embodiment. When speaking, NAO communicated using expressive and animated body language that corresponded

Figure 2.1: Illustration of experimental set up for talking to a humanoid social robot.

to the spoken content and NAO's physical capabilities. NAO's movements were self-initiated based on NAO's demo software.

In the third experiment, NAO was further programmed to nod its head every few seconds when "listening" to the human participant speak. This change was implemented to reduce the variance in embodiment/listener cues between the humanoid social robot and the human agent.

NAO's joints are often noisy, and since this sort of noise is not ambient it can be captured as an acoustic sound. Therefore, when participants were talking, NAO's animated movements were limited to simulated breathing and gentle head nods to reduce the chance of noise coming from NAO's joints.

Human Agent

This treatment consists of the experimenter (GL) as an elicitor, taking an active part in the experimental manipulation. The human agent was a PhD student at the University of Glasgow, a Caucasian male in his late twenties with dark brown hair and a beard. Throughout the entire study, he consistently wore the same outfit (refer to Figure 2.2). This treatment was naturally manipulated by the agent's human looks, voice, and gestures (e.g., nodding) (see Figure 2.2). The human gestures were not planned or controlled and followed his natural embodiment and behaviour to ensure that his body language will stay natural and will correspond to the embodiment of human communication patterns. However, the experimenter did not speak when participants were answering questions, to more closely reflect the conversation scenarios with the other two agents. This treatment was identical in all of the three experiments and the questions asked by the human agent followed the same script when communicating the questions. In order to draw causal inferences and to be able to claim that there were no anecdotal deviations in the agents' behaviour or communication that might affect the results, the human agent had to be a bit more "robotic" and follow a script, like an actor. At the same time, the same script that the human agent used was also used by the humanoid social robot and the disembodied agent, thus minimising any confounding gross communication differences between the agents.

Having multiple experimenters acting as the human agent would have provided a more inclusive representation of human embodiment. However, employing a single experimenter ensures methodological consistency. By maintaining a single agent, confounding factors are minimized, allowing for more accurate comparisons with the two other agents. This approach provides a reliable and standardized framework that increases the validity of the experiment's results.

Figure 2.2: Illustration of experimental set up for talking to the human agent.

Disembodied Agent

This treatment condition featured a “Google Nest Mini” voice assistant. A voice assistant is a particular software in a speaker (in the context of this study, a ”Google Nest Mini” device). It has a minimal physical presence and is disembodied, in that it is not designed for visual interaction (i.e., it does not demonstrate any sort of visual cues), and its verbal cues are limited to clear manifest cues (“I understand”, “Okay, I see”), rather than natural implicit cues (e.g., “ahh”, “amm”) (see Figure 2.3). The voice assistant was also controlled by the experimenter (GL) via the WoZ technique. All questions and speech items were written and coded to a ”ColorNote” application on an Android tablet. Using Bluetooth technology and Android’s accessibility ”select to speak” feature, the experimenter controlled the disembodied voice assistant by streaming questions and speech items to participants. Accordingly, the procedure followed clear pre-programmed protocol where the experimenter did not need to speak or type anything during the interaction but only press a button to start the interaction. The device was used as a Bluetooth speaker, the WiFi function of the device and the microphone were disabled to maintain participants’ privacy. Participants were explicitly told that the disembodied agent’s software was developed by the lab and has no connection to Google, and the device’s WiFi function is not working.

2.2.4 Measurements

Subjective Self Disclosure

Participants were requested to report their level of subjective self-disclosure via the sub-scale of work and studies disclosure in Jourard’s Self-Disclosure Questionnaire (Jourard, 1971). This questionnaire was adapted and adjusted for the context of the study, addressing the statements to student experience in the first experiment, and general life experiences in the second and third experiments. The measurement included ten self-reported items for which participants reported the extent to which they disclosed information to one of the agents on a scale of one (not at all) to seven (to a great extent). The scale was found to be reliable in Experiments 1, 2 and 3 when applied to all of the agents. In the second experiment, the reliability score of the scale when applied to the human agent was only moderate (see Table 2.1).

Disclosure Content

The recordings were automatically processed using a speech recognition package for Python (Zhang, 2017). The text was manually checked and fixed by the re-

Figure 2.3: Illustration of experimental set up for talking to the voice assistant (Google Nest Mini).

	Experiment 1			Experiment 2			Experiment 3		
	Subjective Self-Disclosure								
Treatment	α	M	SD	α	M	SD	α	M	SD
Robot	.94	3.30	1.56	.78	3.87	.88	.84	3.26	1.02
Human	.91	3.76	1.59	.68	4.12	.82	.85	3.63	1.10
DA	.90	2.84	1.35	.87	2.97	1.07	.88	2.98	1.13
Total	-	3.30	1.53	-	3.65	1.04	-	3.29	1.11

Table 2.1: Reliability scores, means and standard deviations of subjective self disclosure scales across the three experiments

searchers to ensure it corresponded accurately to the recordings. The following measurements were extracted from the recordings' content:

- Length of the Disclosure: The volume of disclosure in terms of the number of words per disclosure. The number of words per disclosure was extracted from the text using a simple length command on Python.

- Compound Sentiment: Using Vader for Python (Hutto & Gilbert, 2014), the disclosures were measured to determine their overall sentiment in terms of positive, neutral, and negative sentiment. The compound sentiment evaluates a disclosure sentiment from negative (-1) to positive (+1), based on the calculated sentiment score (see Hutto & Gilbert, 2014).

- Sentimentality: The ratio of overall demonstrated sentiment, positive and negative, in each disclosure. This was calculated based on the combined scores of Vader's (Hutto & Gilbert, 2014) positive and negative sentiments.

Voice Acoustics Features

Basic prosody features are conveyed with changes in pitch, voice intensity, harmonicity, duration, speech rate and pauses (Crystal & Quirk, 1964; Pittam, 2020; Weiss, 2019). For the scope of this study, we decided to focus on the following fundamental features for demonstrating basic differences in voice production and changes mean values of fundamental voice signals within a disclosure.

The features were extracted and processed using Parselmouth (Jadoul, Thompson, & de Boer, 2018), a Python library for Praat (Boersma & Weenink, 2001). The extracted features were:

- Mean pitch - in hertz (Hz).

- Mean harmonicity - the degree of acoustic periodicity in decibels (dB).

- Mean intensity - the loudness of the sound wave in dB.

- Energy - air pressure in voice, measured as the square of the amplitude multiplied by the duration of the sound.

- Duration of speech in seconds.

Other variables

- Agency and Experience: Research into mind perception entails that agency (the ability of the agent to plan and act) and experience (the ability of the agent to sense and feel) are the two key dimensions when valuing an agent's mind (H. M. Gray et al., 2007). To determine whether a difference in mind perception emerged between the agents, after each interaction participants were requested to evaluate the agent in terms of experience and agency, after being introduced to these terms (adapted from (H. M. Gray et al., 2007)). Both concepts were evaluated by the participants using a 0 to 100 rating bar.

- Perceived Stress Scale: This scale was added to the second and third experiments. Participants were requested to report their periodic stress on ten statement items of the perceived stress scale (Cohen, Kamarck, & Mermelstein, 1983), evaluating these on a scale of 1 (never) to five (very often). The scale was found to be reliable in the second ($\alpha = .93$, $M = 2.76$, $SD = .92$), and third ($\alpha = .88$, $M = 3$, $SD = .73$) experiments.

- Extraversion: This measurement was added to the third and final experiment. Participants were asked to rank their extraversion on a scale of 1 (Not at all) to 9 (Very applicable) on the 8 extraversion items of the Mini-Markers Big Five personality scale (Saucier, 1994). The scale was found reliable ($\alpha = .86$, $M = 5.58$, $SD = 1.43$).

- Demographics: Participants across all three experiments were requested to complete a short questionnaire that gathered information on demographic parameters including age, biological sex, gender identification, level of education, nationality, job, previous experience with robots, and whether English is their native language.

2.2.5 Instruments and data preparation

The audio data were recorded using UMT800 by Microtech Gefell, a microphone known for its high sensitivity and outstanding signal-to-noise ratio. We used this device in an acoustic recording laboratory to ensure high quality of audio recordings and minimize any potential effect of noise. We reduced the microphone sensitivity by 10 dB to ensure that loud noises coming from the floor would not be amplified, ensuring that we were able to capture each participant's voice over any other sources of noise. We ensured that the agents were far enough from the microphone so that any other potential source of noise coming from the agents (e.g., the sound of the robot's motors) did not suppress or otherwise interfere with each participant's voice.

When processing the recordings, we reduced noise by using spectral subtraction noise reduction method (Boll, 1979) for reducing the spectral effects of acoustically added noise in speech. A sample of recordings was manually checked to make sure that there is no apparent noise when participants speak and during silent breaks.

2.2.6 Procedure

All three experiments took place in a sound-isolated recording laboratory at the Institute of Neuroscience and Psychology at the University of Glasgow (See Figure

Figure 2.4: The experiment settings at the sound-isolated recording laboratory.

2.4). The recording room was completely soundproof to ensure the highest possible sound quality for the recordings to facilitate offline analyses. The participants booked their desired time-slot for participation using the University of Glasgow subject pool website, and were picked up by one of the experimenters from the building's waiting room. The experiment took approximately 30 minutes per participant. In the first and third experiments, a single experimenter (GL) operated all experimental procedures, and in the second experiment, two experimenters (GL and JNG) operated the experimental procedure. The experimenter(s) sat near a desk outside of the recording room, where the participant could not see them. However, the recording room had a window that provided both parties the option to communicate with each other if needed. The experiment was administered using a "formR" application (Arslan, Walther, & Tata, 2020; Arslan, Tata, & Walther, 2018) that randomized the treatments automatically.

All participants across all three experiments received the same introduction and were told that the humanoid social robot and the disembodied agent were functioning autonomously, and that while we were indeed recording the interaction, and planned to use the data for the analysis, it would be fully anonymised and the experimenter(s) would not actively listen to their disclosures when talking to the robot and the disembodied agent. The participants were further told that the experimenter(s) will only actively listen during their disclosures with the robot and the disembodied agent in case during the interaction there will be no indication of sound from the recording booth (and then the experimenter(s) would need to check in on them and the agent to see whether there was a technical failure or if the participant stopped talking for a specific reason), or in case the participant actively tries to reach the experimenter's attention through the window. The experimenters were following the interaction using sound indication from the recording booth. Participants were explicitly told that the disembodied agent's software was developed by the lab and has no connection to Google, and the device's WiFi function is not working.

After each interaction participants were requested to evaluate the agent in terms of agency and experience. In the first and second experiments, after all interactions, participants evaluated their perceived self-disclosure (Jourard, 1971) to each of the agents. In the third experiment, after each interaction, participants evaluated their perceived self-disclosure to each of the agents via the same instrument (Jourard, 1971). Finally, after all interactions, participants were requested to complete a short questionnaire, reporting demographic parameters, and their previous experience with robots (see section 2.2.4). In the second and third experiments participants then answered the perceived stress scale (Cohen et al., 1983), and in the third experiment participants also answered the extraversion items of the Mini-Markers Big Five personality scale (Saucier, 1994).

Upon completing the experimental procedures, participants were debriefed about the aims of the study and were told that the robot and the disembodied agent were pre-programmed. Then, participants received payment of 3£ (rate of 6£ for one hour) or participation credits. All interactions between participants and the agents (humanoid social robot /human /disembodied agent) were audio recorded for analysis purposes, extracting content and acoustic features from the audio files.

Experiment 1

All participants interacted with each of the three agents, and the order of interaction was randomly assigned across participants. They were asked one question from each agent about each of the three topics: (1) academic assessment, (2) student finances, and (3) university-life balance. The questions were randomly ordered and allocated to the agents. All questions were the same across the agent treatments.

Experiment 2

As with the first experiment, all participants interacted with all agents, in a randomised order. Participants were asked two questions by each agent: (1) work situation, (2) financial habits, (3) social life, (4) family matters, (5) romantic relationships, and (6) hobbies and spare time. The questions were randomly ordered and allocated to the agents. The questions were grouped into three topics: (1) work and finances (questions 1 and 2), (2) social life and leisure time (questions 3 and 6), and (3) intimate and family relationships (questions 4 and 5). All questions were the same across the agent treatments.

Experiment 3

As with the first and second experiments, participants in Experiment 3 interacted with all three agents, in a randomized order. Participants were asked two questions by each agent about each of the three topics: (1) work and life balance (one question about one's work situation, and one question about their spare time and hobbies), (2) relationships and social life (one question about one's closest relationships, and one question about socializing habits), and (3) physical and mental health (one question about habits of sustaining physical health, and one question about habits of sustaining/treating mental health). The topics were randomly allocated to the agents, and the questions within each topic were randomly ordered. All questions were the same across the agent treatments.

2.3 Results

	Experiment 1				Experiment 2				Experiment 3			
	Treatment Agents											
Variable	*df*	*F*	*p*	ω^2	*df*	*F*	*p*	ω^2	*df*	*F*	*p*	ω^2
Subjective Self-Disclosure	(1.37, 34.13)	6.34	.010*	.12	(1.66, 43.06)	17.28	.001***	.29	(1.84, 110.50)	12.47	.001***	.11
Length	(1.26, 31.57)	2.55	.114	.04	(1.36, 35.42)	18.60	.001***	.30	(2, 120)	12.87	.001***	.12
Compound Sentiment	(1.35, 33.62)	.39	.596	-.02	(2, 52)	5.90	.005**	.11	(1.79, 107.24)	.46	.613	-.01
Sentimentality	(2, 50)	.06	.943	-.03	(1.65, 42.78)	.40	.636	-.02	(1.85, 110.77)	1.57	.213	.01
Pitch	(1.65, 41.16)	2.57	.098	.04	(1.62, 42.02)	7.77	.003**	.14	(1.55, 93)	76.49	.001***	.45
Harmonicity	(2, 50)	2.12	.131	.03	(2, 52)	13.60	.001***	.24	(2, 120)	22.75	.001***	.19
Intensity	(2, 50)	2.08	.135	.03	(2, 52)	1.73	.188	.02	(1.48, 88.64)	2.09	.143	.01
Energy	(1.23, 30.79)	1.70	.204	.02	(1.07, 27.73)	1.05	.319	.00	(1, 60.02)	1.09	.300	.00
Duration	(1.19, 29.71)	1.22	.287	.01	(1.38, 35.84)	12.70	.001***	.22	(2, 120)	4.85	.009**	.04

* = $p < .05$, ** = $p < .01$, *** = $p < .001$

Table 2.2: Univariate Results with agents' embodiment as repeated measures treatment

2.3.1 Differences in agency and experience

Doubly multivariate analysis of variance was conducted for each of the experiments to determine whether a difference in agency and experience emerged within the different agents (humanoid social robot vs. human vs. disembodied agent).

Experiment 1

The model was found to be statistically significant, $Wilk's \quad \Lambda = .15$, $p < .001$, suggesting that a difference emerged in the combined value of agency and experience across the three agents. The agents' treatments elicited statistically significant large differences in people's perceptions of the agents sense of agency ($F(2, 50) = 16.32$, $p < .001$, $\omega^2 = .28$) and the agents' demonstration of experience ($F(1.61, 40.17) = 48.91$, $p < .001$, $\omega^2 = .55$). Post hoc analyses using Bonferroni correction revealed that people perceived a human to have higher agency and experience than a humanoid social robot and a disembodied agent (See Figures 2.5 and 2.6). The difference in people's perceptions of agency between a humanoid social robot and a disembodied agent was not statistically significant (see Figure 2.5). People perceived a humanoid social robots to demonstrate higher levels of experience compared to a disembodied agent (see Figure 2.6).

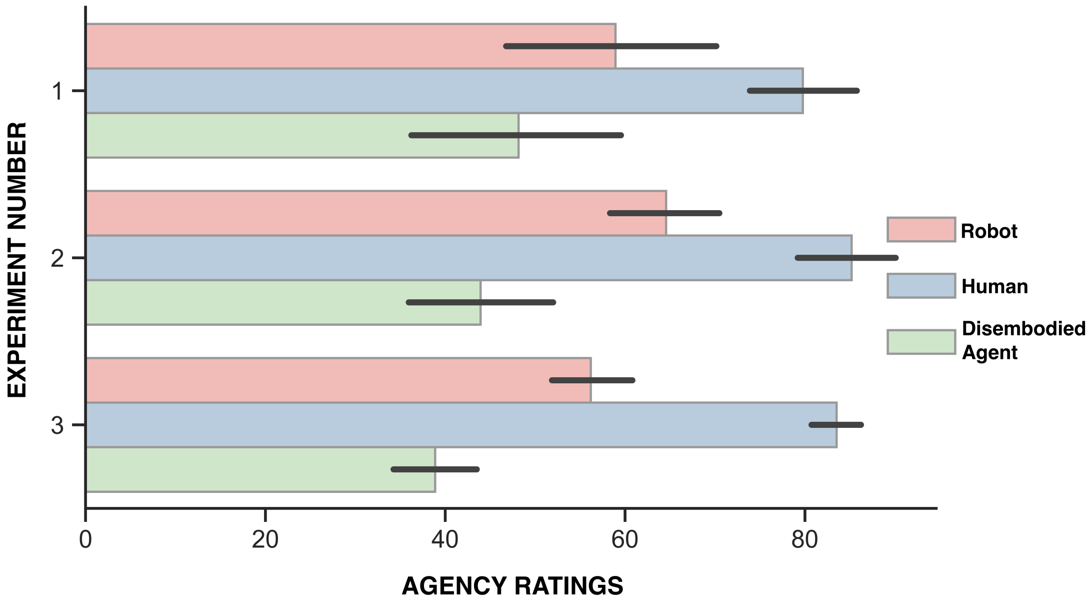

Figure 2.5: Mean score of agency perceptions reported for each agent across the three experiments. The error bars represent $95\% CI$ of the mean score of agency perceptions.

Experiment 2

The model was found to be statistically significant, $Wilk's \quad \Lambda = .14$, $p < .001$, suggesting that a difference emerged in the combined value of agency and experience across the three agents. The agents' treatments elicited statistically significant large differences in people's perceptions of the agents sense of agency ($F(1.61, 41.86) = 21.71$, $p < .001$, $\omega^2 = .34$) and the agents' demonstration of

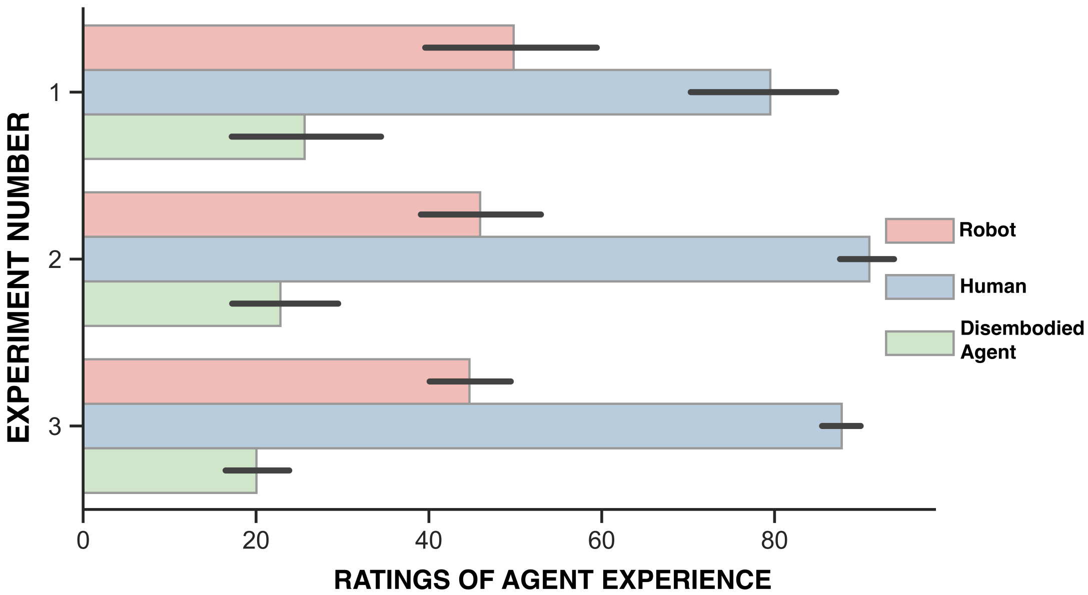

Figure 2.6: Mean score of experience perceptions reported for each agent across the three experiments. The error bars represent 95%CI of the mean score of experience perceptions.

experience ($F(2, 52) = 79.20$, $p < .001$, $\omega^2 = .66$). Post hoc analyses using Bonferroni correction revealed that people perceived a human to have higher agency and experience than a humanoid social robot and a disembodied agent(See Figures 2.5 and 2.6). Moreover, people perceived a humanoid social robot to have higher agency than a disembodied agent (See Figure 2.5). Finally, people perceived a humanoid social robots to demonstrate higher levels of experience compared to a disembodied agent (see Figure 2.6).

Experiment 3

The model was found to be statistically significant, $Wilk's \quad \Lambda = .11$, $p < .001$, suggesting that a difference emerged in the combined value of agency and experience across the three agents. The agents' treatments elicited statistically significant large differences in people's perceptions of the agents sense of agency ($F(2, 120) = 77.33$, $p < .001$, $\omega^2 = .46$) and the agents' demonstration of experience ($F(1.79, 107.40) = 197.93$, $p < .001$, $\omega^2 = .68$). Post hoc analyses using Bonferroni correction revealed that people perceived a human to have higher agency and experience than a humanoid social robot and a disembodied agent(See Figures 2.5 and 2.6). Moreover, people perceived a humanoid social robot to have higher agency than a disembodied agent (see Figure 2.5). Finally, people perceived a humanoid social robots to demonstrate higher levels of experience compared to a disembodied agent (see Figure 2.6).

2.3.2 The effect of agents on disclosure

Doubly multivariate analysis of variance was conducted for each of the experiments to determine whether a difference in disclosure emerged within the different agents (humanoid social robot vs. human vs. disembodied agent), measured in terms of subjective self – disclosure and objective disclosure (length of the disclosure, compound sentiment, sentimentality, pitch, harmonicity, intensity, energy, and duration of the disclosures).

Experiment 1

The model was found to be statistically significant, $Wilk's \quad \Lambda = .06$, $p < .001$, suggesting that a difference emerged in the combined disclosure (in terms of subjective and objective disclosure) across the three agents.

The agents' treatments elicited statistically significant medium to large differences in subjective self-disclosure. Univariate tests revealed statistically nonsignificant differences within the agents in terms of the length of the disclosure, compound sentiment, sentimentality, pitch, harmonicity, intensity, energy, and duration (see Table 2.2).

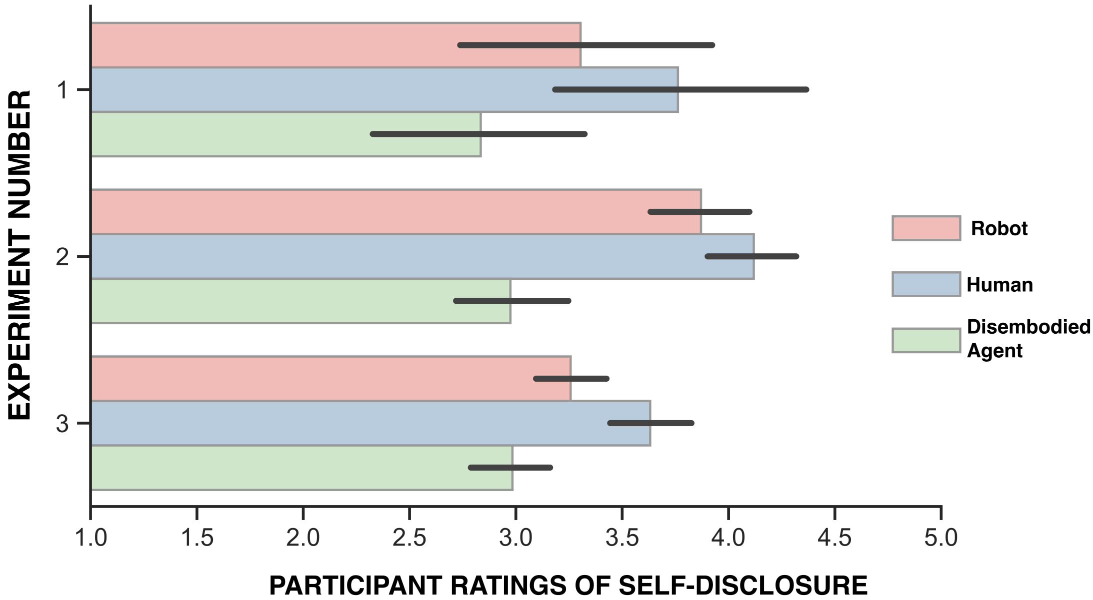

Figure 2.7: Mean score of subjective self-disclosure toward each agent across the three experiments. The error bars represent $95\% CI$ of the mean score of subjective self-disclosure across participants.

Post hoc analyses using Bonferroni correction revealed that people perceived that they disclosed more information to a human than to a humanoid social robot and to a disembodied agent. Nevertheless, there were no significant differences in the way people perceived their disclosures to a humanoid social robot compared to a disembodied agent (see Figure 2.7). Moreover, the pitch of people's voices was higher when talking to a humanoid social robot compared to when talking to a disembodied agent but not compared to when talking to a human (see Table 2.3).

	Experiment 1		Experiment 2		Experiment 3	
Variable	*M* (*SE*)	95%*CI*	*M* (*SE*)	95%*CI*	*M* (*SE*)	95%*CI*
Subjective Self-Disclosure						
Robot	3.30 (.31)	[2.67, 3.94]	3.87 (.17)	[3.52, 4.22]	3.26 (.13)	[3.00, 3.52]
Difference to Human	-.46 (.17)*	[-.90, -.01]	-.25 (.15)	[-.64, .14]	-.37 (.13)*	[-.69, -.06]
Human	3.76 (.31)	[3.12, 4.40]	4.12 (.16)	[3.80, 4.44]	3.63 (.14)	[3.35, 3.91]
Difference to DA	.93 (.33)*	[.08, 1.78]	1.14 (.20)***	[.62, 1.67]	.65 (.15)***	[.28, 1.02]
DA	2.84 (.27)	[2.29, 3.38]	2.97 (.21)	[2.55, 3.40]	2.98 (.15)	[2.69, 3.27]
Difference to Robot	-.47 (.25)	[-1.12, .18]	-.90 (.25)**	[-1.53, -.26]	-.27 (.11)	[-.55, .00]
Length						
Robot	96.50 (22.57)	[50.03, 142.97]	46.15 (3.86)	[38.22, 54.08]	85.83 (10.65)	[64.52, 107.14]
Difference to Human	-35.23 (20.52)	[-87.89, 17.43]	-42.52 (9.52)***	[-66.87, -18.17]	-41.41 (10.18)***	[-66.49, -16.33]
Human	131.73 (27.50)	[75.09, 188.37]	88.67 (10.04)	[68.03, 109.31]	127.24 (10.05)	[107.13, 147.35]
Difference to DA	41.50 (25.27)	[-23.34, 106.34]	41.63 (8.91)***	[18.84, 64.42]	42.71 (9.26)***	[19.91, 65.51]
DA	90.23 (16.18)	[56.92, 123.54]	47.04 (5.25)	[36.25, 57.82]	84.53 (8.26)	[68, 101.05]
Difference to Robot	-6.27 (10.97)	[-34.42, 21.88]	.89 (4.53)	[-10.70, 12.48]	-1.30 (9.27)	[-24.12, 21.52]
Compound Sentiment						
Robot	.64 (.08)	[.47, .80]	.67 (.05)	[.57, .77]	.76 (.04)	[.69, .84]
Difference to Human	-.08 (.11)	[-.36, .20]	-.11 (.07)	[-.28, .07]	-.04 (.06)	[-.18, .09]
Human	.72 (.08)	[.55, .89]	.78 (.05)	[.67, .88]	.81 (.04)	[.73, .88]
Difference to DA	.06 (.11)	[-.23, .35]	.25 (.07)**	[.07, .44]	.01 (.04)	[-.09, .11]
DA	.65 (.08)	[.49, .82]	.52 (.07)	[.39, .66]	.80 (.03)	[.74, .85]
Difference to Robot	.02 (.05)	[-.12, .15]	-.15 (.08)	[-.36, .06]	.03 (.04)	[-.07, .14]
Sentimentality						
Robot	.18 (.02)	[.13, .22]	.25 (.02)	[.21, .29]	.29 (.01)	[.27, .31]
Difference to Human	-.01 (.02)	[-.07, .05]	.02 (.02)	[-.03, .07]	.02 (.01)	[-.01, .05]
Human	.18 (.02)	[.15, .22]	.23 (.01)	[.20, .26]	.27 (.01)	[.25, .29]
Difference to DA	.00 (.03)	[-.07, .08]	-.00 (.03)	[-.08, .07]	.00 (.01)	[-.03, .03]
DA	.18 (.02)	[.13, .23]	.23 (.03)	[.18, .29]	.27 (.01)	[.25, .29]
Difference to Robot	.01 (.02)	[-.06, .07]	-.02 (.03)	[-.10, .06]	-.02 (.01)	[-.04, .01]
Pitch						
Robot	213.20 (10.31)	[191.95, 234.45]	233.45 (8.69)	[215.59, 251.31]	267.50 (8.20)	[251.10, 283.90]
Difference to Human	9.92 (6.23)	[-6.06, 25.90]	19.35 (7.33)*	[.58, 38.11]	55.24 (6.08)***	[40.25, 70.22]
Human	203.28 (12.79)	[176.95, 229.62]	214.10 (5.85)	[202.07, 226.13]	212.27 (6.48)	[199.31, 225.23]
Difference to DA	5.59 (8.56)	[-16.38, 27.55]	1.81 (4.57)	[-9.89, 13.50]	1.46 (3.48)	[-7.12, 10.04]
DA	197.70 (7.20)	[182.86, 212.53]	212.30 (7.03)	[197.84, 226.75]	210.80 (5.79)	[199.23, 222.38]
Difference to Robot	-15.51 (5.67)*	[-30.06, -.96]	-21.15 (5.61)**	[-35.51, -6.79]	-56.70 (5.73)***	[-70.81, -42.59]
Harmonicity						
Robot	11.98 (.55)	[10.84, 13.12]	10.40 (.40)	[9.59, 11.22]	10.14 (.26)	[9.61, 10.66]
Difference to Human	-.52 (.29)	[-1.27, .23]	1.12 (.31)**	[.33, 1.91]	-.54 (.17)**	[-.94, -.13]
Human	12.50 (.55)	[11.38, 13.62]	9.28 (.54)	[8.17, 10.40]	10.67 (.25)	[10.17, 11.17]
Difference to DA	-.02 (.33)	[-.88, .83]	-1.42 (.29)***	[-2.17, -.67]	-.68 (.19)**	[-1.13, -.22]
DA	12.52 (.68)	[11.13, 13.91]	10.70 (.48)	[9.72, 11.68]	11.35 (.28)	[10.79, 11.90]
Difference to Robot	.54 (.26)	[-.13, 1.22]	.30 (.26)	[-.36, .96]	1.21 (.19)***	[.75, 1.67]
Intensity						
Robot	66.47 (.55)	[65.33, 67.61]	72.06 (.56)	[70.92, 73.21]	53.59 (.30)	[53, 54.19]
Difference to Human	.83 (.54)	[-.55, 2.21]	.93 (.56)	[-.51, 2.37]	.31 (.38)	[-.62, 1.25]
Human	65.64 (.42)	[64.77, 66.51]	71.14 (.64)	[69.82, 72.45]	53.28 (.43)	[52.42, 54.14]
Difference to DA	-1.02 (.45)	[-2.19, .14]	-.59 (.55)	[-2, .83]	.35 (.36)	[-.54, 1.23]
DA	66.66 (.57)	[65.49, 67.84]	71.72 (.59)	[70.51, 72.94]	52.93 (.33)	[52.27, 53.59]
Difference to Robot	.20 (.60)	[-1.34, 1.73]	-.34 (.38)	[-1.30, .63]	-.66 (.21)**	[-1.17, -.15]
Energy						
Robot	.62 (.24)	[.13, 1.11]	.50 (.07)	[.36, .65]	.02 (.00)	[.01, .02]
Difference to Human	.16 (.17)	[-.27, .59]	-1.28 (1.13)	[-4.17, 1.61]	-.19 (.18)	[-.63, .25]
Human	.46 (.10)	[.26, .66]	1.78 (1.13)	[-.55, 4.11]	.20 (.18)	[-.15, .56]
Difference to DA	-.27 (.18)	[-.71, .18]	1.03 (1.14)	[-1.88, 3.95]	.19 (.18)	[-.26, .62]
DA	.73 (.24)	[.22, 1.23]	.75 (.26)	[.21, 1.29]	.02 (.00)	[.01, .03]
Difference to Robot	.11 (.07)	[-.07, .28]	.25 (.24)	[-.36, .86]	.00 (.00)	[-.00, .01]
Duration						
Robot	47.33 (10.17)	[26.39, 68.28]	19.90 (1.79)	[16.23, 23.57]	39.66 (4.35)	[30.95, 48.36]
Difference to Human	-12.02 (9.71)	[-36.93, 12.89]	-12.33 (3.22)**	[-20.56, -4.10]	-9.48 (4.08)	[-19.52, .55]
Human	59.35 (14.04)	[30.43, 88.28]	32.23 (3.90)	[24.21, 40.25]	49.14 (4.22)	[40.71, 57.57]
Difference to DA	13.77 (12.51)	[-18.32, 45.87]	10.70 (2.90)**	[3.28, 18.11]	10.94 (3.82)*	[1.52, 20.36]
DA	45.58 (7.38)	[30.39, 60.77]	21.53 (2.41)	[16.59, 26.48]	38.20 (3.27)	[31.67, 44.73]
Difference to Robot	-1.75 (5.00)	[-14.59, 11.08]	1.64 (1.57)	[-2.38, 5.65]	-1.46 (3.52)	[-10.13, 7.22]

Multiple comparisons were adjusted using Bonferroni correction. * = $p < .05$, ** = $p < .01$, *** = $p < .001$

Table 2.3: Estimated marginal means and multiple pairwise comparisons between the agents

Experiment 2

The model was found to be statistically significant, $Wilk's \quad \Lambda = .08$, $p = .005$, suggesting that a difference emerged in the combined disclosure (in terms of subjective and objective disclosure) across the three agents. The order of the questions was found to not have a significant effect in terms of the combined disclosure, $Wilk's \quad \Lambda = .72$, $p = .506$, and neither did the interaction of the agents' treatments with the order of the questions, $Wilk's \quad \Lambda = .29$, $p = .185$.

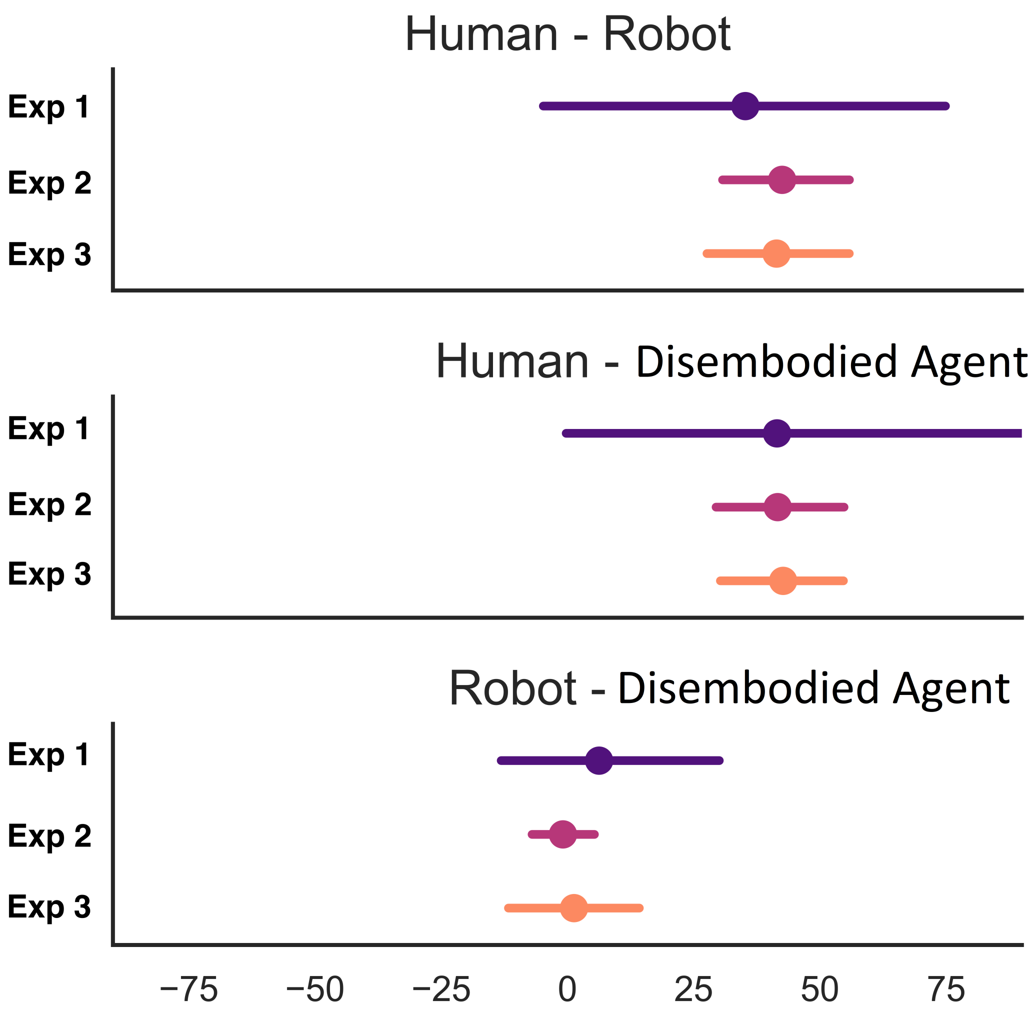

Figure 2.8: Length differences between different agent pairs, across three experiments. The Y-axis groups disclosure lengths by experiment number, and the x-axis shows the mean difference between disclosure length between the two agents indicated in each subtitle. The error bars represent $95\% CI$ of the mean score of length differences between the two agents.

The agents' treatments elicited statistically significant large differences in subjective self-disclosure, length, duration, pitch, and harmonicity of the disclosure. Moreover, the agents' treatments elicited statistically significant medium to large

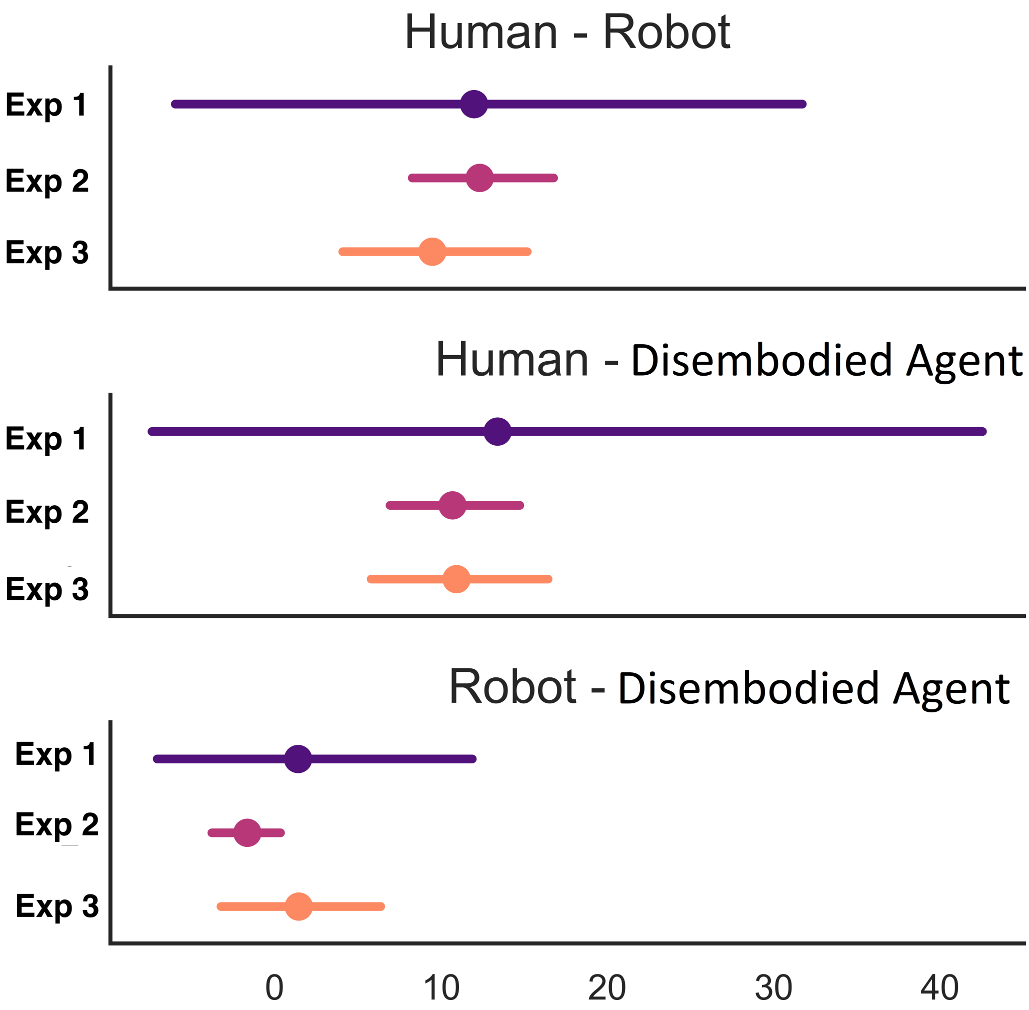

Figure 2.9: Duration differences between different agent pairs, across three experiments. The Y-axis groups disclosure duration by experiment number, and the x-axis shows the mean duration differences between the two agents indicated in each subtitle. The error bars represent $95\% CI$ of the mean score of duration differences between the two agents.

differences in the disclosures' compound sentiment. Univariate tests revealed that the differences within the agents in terms of the sentimentality, intensity, and energy of the disclosures were not statistically significant (see Table 2.2).

Post hoc analyses using Bonferroni correction revealed that people perceived that they disclosed less information to a disembodied agent than to a human or a humanoid social robot. Nevertheless, there were no significant differences in the way people perceive their disclosures to a humanoid social robot compared to a human (see Figure 2.7). Furthermore, people's disclosures were longer in the number of words shared and duration when disclosing to a human than to a humanoid social robot or a disembodied agent. There were no statistically significant differences in disclosures' length or duration between disclosures to a humanoid social robot and to a disembodied agent (See Figures 2.8 and 2.9).

The pitch of people's voices was higher when talking to a humanoid social robot compared to when talking to a human or to a disembodied agent. No statistically significant differences in voice pitch emerged when talking to a human compared to a disembodied agent. People's voices were also less harmonious when talking to a human compared to a humanoid social robot or a disembodied agent, however, the difference in harmonicity between people's voices when talking to humanoid social robot and to a disembodied agent did not reach statistical significance (see Table 2.3).

Experiment 3

The model was found to be statistically significant, $Wilk's \quad \Lambda = .14$, $p < .001$, suggesting that a difference emerged in the combined disclosure (in terms of subjective and objective disclosure) across the three agents. The order of the questions was found to not have a significant effect in terms of the combined disclosure, $Wilk's \quad \Lambda = .76$, $p = .056$, and so is the interaction of the agents' treatments with the order of the questions, $Wilk's \quad \Lambda = .68$, $p = .322$.

The agents' treatments elicited statistically significant large differences in the disclosures' pitch and harmonicity. Moreover, the agents' treatments elicited statistically significant medium to large differences in subjective self-disclosure and in the length of the disclosures, in addition to a small to medium difference in the duration of the disclosures. Univariate tests reveal that the differences within the agents in terms of the compound sentiment, sentimentality, intensity, and energy of the disclosures were not statistically significant (see Table 2.2).

Post hoc analyses using Bonferroni correction reveal that people perceived that they disclosed more information to a human than to a humanoid social robot or a disembodied agent. Nevertheless, there are no significant differences in the way people perceived their disclosures to a humanoid social robot compared to a disembodied agent (see Figure 2.7). Furthermore, people's disclosures were longer in the number of words shared when disclosing to a human than to a humanoid social robot or a disembodied agent. No statistically significant differences emerged among disclosure length between humanoid social robots and disembodied agents (See Figure 2.8). In terms of the disclosures' duration, people talk longer to a human than to a disembodied agent, whereas there are no statistically significant differences in disclosures' duration within disclosures to a humanoid social robot and a human and also to a disembodied agent (See Figure 2.9).

The pitch of people's voices was higher when talking to a humanoid social robot compared to when talking to a human or to a disembodied agent. There are no statistically significant differences in peoples' pitch when talking to a human compared to a disembodied agent. People's voice is more harmonious when talking to a disembodied agent compared to a humanoid social robot or a human, and also it is more harmonious when talking to a humanoid social robot than to a human. In terms of the disclosures' voice intensity, people talk louder to a humanoid social robot than to a disembodied agent, whereas there are no statistically significant differences in the disclosures' voice intensity within disclosures to a humanoid social robot and a human and also within a human to a disembodied agent (see Table 2.3).

2.3.3 The effect of topics of disclosure on disclosure

	Experiment 1				Experiment 2				Experiment 3			
	Topics of Disclosure											
Variable	*df*	*F*	*p*	ω^2	*df*	*F*	*p*	ω^2	*df*	*F*	*p*	ω^2
Subjective Self-Disclosure	(2, 50)	2.69	.078	.04	(2, 52)	.37	.695	-.02	(2, 120)	.14	.870	-.01
Length	(1.47, 44.78)	.90	.386	-.00	(2, 52)	1.68	.196	.02	(2, 120)	4.05	.020*	.03
Compound Sentiment	(2, 50)	6.52	.003**	.12	(2, 52)	5.29	.008**	.10	(1.96, 106.98)	6.61	.003**	.06
Sentimentality	(2, 50)	2.55	.088	.04	(1.64, 42.55)	14.23	.001***	.25	(2, 120)	.69	.506	-.00
Pitch	(1.30, 32.56)	.69	.448	-.01	(1.62, 42.07)	1.22	.300	.01	(2, 120)	.61	.544	-.00
Harmonicity	(2, 50)	.52	.597	-.01	(2, 52)	1.92	.156	.02	(2, 120)	.74	.480	-.00
Intensity	(2, 50)	.57	.568	-.01	(1.63, 42.42)	.12	.848	-.02	(1.85, 110.78)	2.24	.115	.01
Energy	(1.60, 40.06)	1.29	.282	.01	(1.08, 28.05)	.72	.414	-.01	(1, 60.02)	1.08	.302	.00
Duration	(1.38, 34.59)	1.39	.257	.01	(2, 52)	1.50	.233	.01	(1.88, 112.48)	5.35	.007**	.05

* = $p < .05$, ** = $p < .01$, *** = $p < .001$

Table 2.4: Univariate Results with disclosure topics as repeated measures treatment.

Doubly multivariate analysis of variance was conducted for each of the experiments to determine whether a difference in disclosure emerged within the different topics of disclosure (see Procedure, section 2.2.6), measured in terms of subjective self – disclosure and objective disclosure (length of the disclosure, compound sentiment, sentimentality, pitch, harmonicity, intensity, energy, and duration of the disclosures).

Experiment 1

The model was found to not be statistically significant, $Wilk's \quad \Lambda = .20$, $p = .200$, suggesting that a difference did not emerge in the combined disclosure (in terms of subjective and objective disclosure) across the three topics (see section 2.2.6).

The topics of disclosure elicited a statistically significant medium to large difference in the disclosures' compound sentiment. Univariate tests revealed that the differences within the topics in terms of subjective self-disclosure, the length, duration, sentimentality, pitch, harmonicity, intensity, and energy of the disclosures were not statistically significant (see Table 2.4).

	Experiment 1		Experiment 2		Experiment 3	
Variable	*M* (*SE*)	95%*CI*	*M* (*SE*)	95%*CI*	*M* (*SE*)	95%*CI*
Subjective Self-Disclosure						
Topic 1	3.67 (.31)	[3.03, 4.31]	3.73 (.19)	[3.34, 4.11]	3.30 (.14)	[3.03, 3.57]
Difference to Topic 2	.53 (.26)	[-.14, 1.20]	.10 (.15)	[-.29, .48]	-.02 (.13)	[-.35, .31]
Topic 2	3.14 (.30)	[2.53, 3.75]	3.63 (.13)	[3.36, 3.90]	3.32 (.14)	[3.04, 3.61]
Difference to Topic 3	.05 (.25)	[-.57, .68]	.02 (.12)	[-.30, .33]	.07 (.14)	[-.27, .41]
Topic 3	3.09 (.29)	[2.49, 3.69]	3.61 (.15)	[3.30, 3.92]	3.25 (.15)	[2.95, 3.55]
Difference to Topic 1	-.58 (.32)	[-1.40, .24]	-.12 (.16)	[-.54, .30]	-.05 (.16)	[-.43, .33]
Length						
Topic 1	120.89 (30.63)	[57.80, 183.97]	63.93 (6.26)	[51.06, 76.79]	97.39 (9.17)	[79.04, 115.73]
Difference to Topic 2	17 (17.50)	[-27.79, 61.79]	-1.35 (7.72)	[-21.11, 18.40]	-17.17 (10.60)	[-43.29, 8.94]
Topic 2	103.89 (21.34)	[59.93, 147.84]	65.28 (7.54)	[49.78, 80.78]	114.56 (12.74)	[89.07, 140.05]
Difference to Topic 3	10.19 (16.80)	[-32.90, 53.29]	12.63 (6.23)	[-3.31, 28.57]	28.91 (11.22)*	[1.27, 56.55]
Topic 3	93.69 (12.58)	[67.78, 119.60]	52.65 (6.40)	[39.50, 65.80]	85.65 (6.99)	[71.66, 99.63]
Difference to Topic 1	-27.19 (25.85)	[-93.51, 39.13]	-11.28 (8.55)	[-33.16, 10.61]	-11.74 (8.65)	[-33.03, 9.56]
Compound Sentiment						
Topic 1	.76 (.06)	[.63, .88]	.55 (.06)	[.44, .69]	.75 (.04)	[.68, .82]
Difference to Topic 2	.27 (.09)*	[.03, .50]	-.18 (.06)*	[-.33, -.03]	-.13 (.04)**	[-.22, -.04]
Topic 2	.49 (.10)	[.28, .70]	.74 (.04)	[.69, .81]	.88 (.02)	[.84, .92]
Difference to Topic 3	-.27 (.09)*	[-.51, -.03]	.06 (.05)	[-.07, .18]	.15 (.04)**	[.04, .25]
Topic 3	.76 (.06)	[.64, .89]	.68 (.05)	[.58, .79]	.73 (.04)	[.66, .81]
Difference to Topic 1	.01 (.07)	[-.17, .18]	.13 (.06)	[-.04, .29]	-.02 (.05)	[-.14, .11]
Sentimentality						
Topic 1	.20 (.02)	[.16, .25]	.20 (.01)	[.17, .22]	.27 (.01)	[.25, .29]
Difference to Topic 2	.05 (.03)	[-.02, .13]	-.03 (.01)*	[-.07, -.00]	-.00 (.01)	[-.04, .03]
Topic 2	.15 (.02)	[.11, .19]	.23 (.01)	[.20, .25]	.27 (.01)	[.25, .29]
Difference to Topic 3	-.04 (.02)	[-.09, .01]	-.06 (.02)**	[-.11, -.01]	-.01 (.01)	[-.04, .02]
Topic 3	.19 (.02)	[.15, .23]	.29 (.02)	[.24, .34]	.28 (.01)	[.26, .30]
Difference to Topic 1	-.01 (.03)	[-.08, .06]	.09 (.02)***	[.04, .15]	.01 (.01)	[-.02, .05]
Pitch						
Topic 1	201.96 (8.59)	[184.26, 219.66]	215.15 (6.18)	[202.44, 227.85]	227.52 (7.52)	[212.47, 242.56]
Difference to Topic 2	-.67 (6.74)	[-17.98, 16.63]	-7.22 (3.62)	[-16.47, 2.04]	-.34 (7.59)	[-19.04, 18.35]
Topic 2	202.63 (9.71)	[182.63, 222.63]	222.36 (7.15)	[207.67, 237.05]	227.86 (7.14)	[213.59, 242.13]
Difference to Topic 3	-6.97 (4.73)	[-19.11, 5.17]	.02 (6.17)	[-15.78, 15.82]	-7.34 (7.27)	[-25.23, 10.56]
Topic 3	209.60 (12.54)	[183.77, 235.42]	222.34 (7.94)	[206.02, 238.66]	235.19 (8.33)	[218.54, 251.85]
Difference to Topic 1	7.64 (9.32)	[-16.28, 31.56]	7.20 (5.86)	[-7.79, 22.18]	7.68 (8.61)	[-13.52, 28.88]
Harmonicity						
Topic 1	12.16 (.61)	[10.91, 13.41]	9.83 (.50)	[8.81, 10.86]	10.67 (.27)	[10.14, 11.20]
Difference to Topic 2	-.30 (.32)	[-1.12, .51]	-.37 (.26)	[-1.04, .29]	-.19 (.23)	[-.75, .36]
Topic 2	12.47 (.60)	[11.24, 13.69]	10.21 (.46)	[9.26, 11.15]	10.86 (.29)	[10.29, 11.44]
Difference to Topic 3	.09 (.31)	[-.71, .88]	-.14 (.27)	[-.84, .56]	.24 (.21)	[-.27, .76]
Topic 3	12.38 (.59)	[11.17, 13.59]	10.35 (.46)	[9.40, 11.29]	10.62 (.25)	[10.11, 11.13]
Difference to Topic 1	.22 (.30)	[-.54, .98]	.51 (.28)	[-.20, 1.22]	-.05 (.19)	[-.52, .43]
Intensity						
Topic 1	65.96 (.50)	[64.92, 67]	71.77 (.54)	[70.67, 72.87]	52.25 (.33)	[52.60, 53.90]
Difference to Topic 2	-.31 (.62)	[-1.90, 1.29]	.15 (.39)	[-.86, 1.16]	-.36 (.36)	[-1.25, .52]
Topic 2	66.27 (.56)	[65.11, 67.43]	71.62 (.59)	[70.40, 72.84]	53.62 (.42)	[52.77, 54.46]
Difference to Topic 3	-.28 (.43)	[-1.38, .82]	.09 (.62)	[-1.50, 1.68]	.69 (.34)	[-.15, 1.52]
Topic 3	66.55 (.51)	[65.51, 67.59]	71.53 (.65)	[70.19, 72.87]	52.93 (.32)	[52.30, 53.56]
Difference to Topic 1	.59 (.58)	[-.89, 2.06]	-.24 (.47)	[-1.46, .97]	-.32 (.27)	[-.98, .33]
Energy						
Topic 1	.48 (.10)	[.28, .69]	.60 (.08)	[.43, .77]	.02 (.00)	[.01, .02]
Difference to Topic 2	-.24 (.17)	[-.66, .19]	-.19 (.26)	[-.85, .47]	-.18 (.18)	[-.62, .26]
Topic 2	.72 (.25)	[.21, 1.23]	.79 (.27)	[.24, 1.34]	.20 (.18)	[-.15, .56]
Difference to Topic 3	-.11 (.10)	[-.14, .36]	-.87 (1.13)	[-3.77, 2.04]	.19 (.18)	[-.25, .63]
Topic 3	.60 (.24)	[.12, 1.09]	1.65 (1.13)	[-.68, 3.98]	.02 (.00)	[.01, .02]
Difference to Topic 1	.12 (.17)	[-.31, .55]	1.05 (1.13)	[-1.83, 3.94]	-.00 (.00)	[-.01, .00]
Duration						
Topic 1	58.56 (15.17)	[27.31, 89.80]	25.40 (2.52)	[20.23, 30.58]	41.98 (3.60)	[34.77, 49.19]
Difference to Topic 2	7.49 (8.06)	[-13.20, 28.17]	-.69 (2.57)	[-7.28, 5.90]	-6.73 (4)	[-16.57, 3.11]
Topic 2	51.07 (9.84)	[30.80, 71.34]	26.09 (3.31)	[19.30, 32.89]	48.71 (5.19)	[38.32, 59.10]
Difference to Topic 3	8.43 (7.54)	[-10.93, 27.78]	3.93 (2.03)	[-1.26, 9.12]	12.41 (4.17)*	[2.15, 22.67]
Topic 3	42.64 (5.25)	[31.83, 53.46]	22.17 (2.40)	[17.23, 27.10]	36.30 (2.70)	[30.89, 41.71]
Difference to Topic 1	-15.91 (12.33)	[-47.56, 15.74]	-3.24 (2.63)	[-9.96, 3.48]	-5.68 (3.16)	[-13.46, 2.10]

Multiple comparisons were adjusted using Bonferroni correction. $^{*} = p < .05$, $^{**} = p < .01$, $^{***} = p < .001$

Table 2.5: Estimated marginal means and multiple pairwise comparisons between the topics of disclosure

Post hoc analyses using Bonferroni correction revealed that people's disclosures were more negative when talking about student finances compared to academic assessment and university-life balance. Nevertheless, there was no significant difference in the compound sentiment within disclosures about academic assessment and disclosures about university-life balance (see Table 2.5).

Experiment 2

The model was found to not be statistically significant, $Wilk's \quad \Lambda = .21$, $p = .172$, suggesting that a difference did not emerge in the combined disclosure (in terms of subjective and objective disclosure) across the three topics (see section 2.2.6). The order of the questions was found to not have a significant effect in terms of the combined disclosure, $Wilk's \quad \Lambda = .52$, $p = .133$, and so was the interaction of the agents' treatments with the order of the questions, $Wilk's \quad \Lambda = .18$, $p = .104$.

The topics of disclosure elicited a statistically significant large difference in the disclosures' sentimentality and a statistically significant medium to large difference in the disclosures' compound sentiment. Univariate tests revealed that the differences within the topics in terms of subjective self-disclosure, the length, duration, pitch, harmonicity, intensity, and energy of the disclosures were not statistically significant (see Table 2.4).

Post hoc analyses using Bonferroni correction revealed that people's disclosures were more sentimental when talking about their intimate and family relationships compared to their social life and leisure time, and their work and financial situation. In addition, people's disclosures were more positive when talking about their social life and leisure time compared to their work and financial situation. Nevertheless, there is no significant difference in the compound sentiment within disclosures about work and financial situation and disclosures about intimate and family relationships, and within disclosures about social life and leisure time and intimate and family relationships (see Table 2.5).

Experiment 3

The model was found to not be statistically significant, $Wilk's \quad \Lambda = .44$, $p = .051$, suggesting that a difference did not emerge in the combined disclosure (in terms of subjective and objective disclosure) across the three topics (see section 2.2.6). The order of the questions was found to not have a significant effect in terms of the combined disclosure, $Wilk's \quad \Lambda = .76$,$p = .056$, and so is the interaction of the agents' treatments with the order of the questions, $Wilk's \quad \Lambda = .79$, $p = .711$.

The topics of disclosure elicited a statistically significant medium difference in the disclosures' compound sentiment, and statistically significant small to medium differences in the disclosures' length and duration. Univariate tests revealed that the differences within the topics in terms of subjective self-disclosure, the sentimentality, pitch, harmonicity, intensity, and energy of the disclosures were not statistically significant (see Table 2.4).

Post hoc analyses using Bonferroni correction revealed that people's disclosures were more positive when talking about their relationships and society compared to their work-life balance and their physical and mental health. Nevertheless, there is no significant difference in the compound sentiment within disclosures about physical and mental health and disclosures about work-life balance. In addition, people's disclosures about relationships and society are longer in length and duration than disclosures about physical and mental health (see Table 2.5).

2.4 Discussion

The study reported here assessed the extent to which disclosures to social robots differ from disclosures to humans and disembodied conversational agents. Across the three laboratory experiments, we provide relatively consistent evidence highlighting that subjective perceptions of self-disclosures differ from objective evidence of disclosure across three agents. Moreover, the results underscore differences in the information elicited by the agents' embodiment compared to the information that is elicited by the conversational topics.

2.4.1 Overall disclosure differs by agent, not topic

The results indicate that, overall, disclosure is influenced more by an agent's embodiment than the disclosure topic. As can be seen in the results across three experiments, differences emerged in the combined disclosure measures across the three agents, whereas no differences emerged in the combined disclosure across three topics. This reveals important insights into the role played by an agent's embodiment in disclosure settings. It demonstrates that an agent's embodiment has wider influence over what people disclose, and how they disclose it, and supports the assumption that different agents elicit different types of information. As can be seen in the following key results, agents' embodiment takes a broader role in disclosures through the way people perceive their disclosures, the amount of information that they disclose, and the way that they communicate it. The results demonstrate substantial differences in the disclosures' sentiment and sentimentality within the topics presented to participants. This is particularly interesting considering that while agents' embodiment influences the way people communicate information, the amount of information they share, and how they perceive their own disclosures - has little to no influence on the actual content that is shared.

These findings expand on the functionalities of social robots as a social communication medium (Zhao, 2006), and the attributes of embodiment that contribute to the "richness" of the medium (Daft & Lengel, 1986). The results suggest that even though the exact content of the questions changed across experiments, the effect of embodiment on key factors of self-disclosure endured, while topics only impacted (in most cases) the sentiment of the disclosure (whether participants shared positive or negative information). Accordingly, we argue that, while the media richness theory (MRT; Daft & Lengel, 1986) was originally proposed with respect to computer mediated communication, it should be studied further in HRI settings. Therefore, it can be concluded that, in line with MRT (Daft & Lengel, 1986), embodiment is a key factor for evaluating responsiveness in HRI, as it extends the abilities of the communication medium (Hoorn, 2018). In contrast to channel activation theory (Carlson & Zmud, 1999), the topics of disclosure are situational, and while these impact the sentiment and sentimentally of the disclosed content, they are not as central in their influence on disclosure as embodiment, in terms of quantity, perceptions, and behaviour. Nevertheless, it is important to note that, by affecting the sentiment and sentimentality of disclosed content, the topic of the disclosure can frame an interaction in a positive or a negative way. Content and context also play a substantial role; like other elicitation procedures and techniques, the discussed content influences the essence of the information that is being shared.

It is also important to remember that interactions between people and artificial agents are influenced by multiple factors beyond an agent's embodiment and the content of conversation. A recent study demonstrated that when interacting with a crowd-operated social robot (where participants knew that real people were talking via the social robot), more participants reported privacy concerns in the experimental condition where only their voice was broadcast to the people operating the social robot, compared to the group of participants whose voice and video were seen by the people controlling the robot (Abbas et al., 2020). These authors consequently suggest that the recording method (i.e., how much information a robot receives or records from a person) can also affect people' responses when communicating with robots. As social robots are gradually becoming integrated as telepresence devices (Hilty et al., 2020) and taking an active role in health interventions (e.g., van Wingerden, Barakova, Lourens, & Sterkenburg, 2020), it will be valuable for future research to consider additional aspects of interactions with social robots, including the form of broadcasting and privacy matters.

2.4.2 Artificial embodiment requires more than stimulus cues

The results clearly and unsurprisingly demonstrate that human embodiment elicits the richest disclosures in terms of quantity of information shared. When participants spoke to another person, their disclosures were longer, in terms of number of words and overall duration, than disclosures to the humanoid robot and the disembodied agent. Moreover, people perceived that they shared more with the human conversational partner than with the robot or disembodied agent. While participants disclosed the most to the agent that looked most like themselves, and with which they were most familiar (i.e., the human experimenter), we did not find that stimulus cues for embodiment influenced differences in disclosure quantity and perception between the humanoid social robot and the disembodied agent. While the results clearly demonstrate that people grasp that a humanoid social robot is different from a disembodied agent, such differences in physical embodiment did not result in differences in amount of information disclosed to these two artificial agents, or participants' perceptions of the quantity or quality of disclosure. Questionnaire ratings revealed that people perceived the humanoid social robot to provide a richer experience and to have higher agency than a disembodied agent, and yet, such perceptions did not directly influence their disclosures.

It can be argued that stimulus cues to agents' embodiment are limited to differences in quantity and perceptions of disclosure to artificial agents. Considering the novelty of interactions with artificial agents for most people (and certainly participants in this study), most people tend to perceive them as some manner of "black box" (Bunge, 1963) and experience some uncertainty about how to behave around them. People might require more substantial information than stimulus cues of (human-like) embodiment to treat an agent as more human-like (Berger & Calabrese, 1975). Whereas human embodiment naturally addresses some uncertainties of behaviour (Berger & Bradac, 1982); it may be the case that varying levels of artificial embodiment do not comply to these rules. Certain behaviours or actions might provide cues or information that extend from the agent's physical embodiment and can support reasoning, mentalizing, and reacting, accordingly (Waytz, Cacioppo, & Epley, 2010; K. Gray et al., 2012; Waytz et al., 2010; Wegner, 2002). Such attributes can provide a sense of intentionality and meaning to agents' behaviour, and would be in line with how humans interact with each other (Wiese et al., 2017).

This finding corresponds to previous reports showing that reactions to artificial agents, triggered by their human-like embodiment, are not solely based on an agent's physical features (e.g., human-like body and face, and human-like gestures)

(Hortensius & Cross, 2018) but are also shaped by human perceivers' prior knowledge (Cross et al., 2016; Klapper et al., 2014; Özdem et al., 2017). Accordingly, we suggest that differences in quantity and perceptions of disclosure within artificial agents are inextricably linked to participants' prior knowledge and expectations about the robot and disembodied agent used here. As such, stimulus cues that endow an artificial agent with human-like features (such as a body with two arms and two legs, and a head) are not enough to trigger people to disclose the same quantity and quality of information to an artificial agent as they do to another person. In addition, it is crucial to take into account that particular visual attributes of embodied artificial agents can impact the manner in which individuals interact with and self-disclose to these agents. Therefore, it could be that some of the effects observed in this study are due to the child-like appearance of Nao. The child-like appearance of certain social robots can have a significant impact on disclosure from both children and adults, as it relates to the "like me" hypothesis (Meltzoff, 2007). The "like me" hypothesis suggests that individuals are more likely to disclose personal information and engage in social interaction with others who are perceived as similar to themselves (Meltzoff & Prinz, 2002; Meltzoff, 2007; Meltzoff, Kuhl, Movellan, & Sejnowski, 2009). In the case of child-like social robots, their appearance may evoke a sense of familiarity and approachability, leading to increased disclosure.

2.4.3 Embodiment cues as gestures of reciprocity

These findings further highlight the role of embodiment as a cue for disclosure reciprocity (Derlega et al., 1973). As people ascribe meaning to agents' actions (Epley & Waytz, 2010; K. Gray et al., 2012; Waytz et al., 2010) they require systematic cues to evaluate the agents' reactions as acts of reciprocity (Firestone, 1977; Argyle & Cook, 1976; Argyle & Dean, 1965; Patterson, 1973). To disclose information, people look for social cues in an agent's embodiment, such as behaviours or gestures, to assess the agents' behaviour and identify its origins (Chaiken, 1980; S. Chen, Duckworth, & Chaiken, 1999; Eagly & Chaiken, 1993). When these cues are limited in conveying the agent's involvement in an interaction (Argyle & Cook, 1976; Argyle & Dean, 1965; Patterson, 1973) and fail to achieve sufficient equilibrium or reciprocity (Argyle & Dean, 1965), one downregulates their own levels of disclosure (Hosman, 1987) and is more likely to withdraw from the interaction (Argyle & Dean, 1965). The results suggest that the limits to embodiment of the artificial agents we used here restricted them from providing sufficient cues of knowledge or understanding when a person is disclosing information (and that human listeners naturally perform to signal reciprocity). Accordingly, participants shared less information with artificial agents, and were aware of this fact.

It should be considered that features of embodiment are dynamic, and while HRI research is often focused on dialogue and gestures, physical and tangible cues can also be effective in promoting self-disclosure. A variety of different physical cues to embodiment serve to signal reciprocation during a conversation, including touch and dynamic gaze, and previous work documents how these cues hold potential to elicit rich disclosures (e.g., Hirano et al., 2018; Iwasaki et al., 2019; Shiomi et al., 2020; Willemse & van Erp, 2019). Hence, a valuable avenue for further investigation will be to examine how disclosure reciprocity can be achieved with variety of embodiment cues, and which of these cues is responsible for a meaningful elicitation.

2.4.4 Subjective perceptions align relatively well with objective data

Subjective perceptions of self-disclosure align relatively well with the objective data and correspond to observed evidence of the length and duration of the disclosure. Across all three experiments, participants perceived that they shared more with the human listener than with a disembodied agent or a humanoid social robot, and analyses of speech volume and content corroborated this perception. This finding is especially interesting considering how reliably the effects of disclosure length and duration replicated across the three experiments, with similar differences in the number of words uttered and seconds spent talking to the three agents. This contradicts Levi-Belz and Kreiner (2016) findings, and provides evidence supporting the notion that people's perceptions of their own disclosures are formed by observing self behaviour (in terms of disclosure volume) and reflecting upon it, rationally (Bem, 1967, 1972).

It is of note that in Experiment 2, participants retrospectively evaluated their perceptions of self-disclosures and perceived that they were sharing more with the humanoid robot than they actually were (compared to the other agents), in terms of the disclosure volume. Therefore, we can assume that when reflecting on interactions retrospectively, it is possible to lose some of our objectivity and perceive our disclosures in line with the way that we perceive or experience the agent, and not in a manner that corresponds to actual behaviour during an interaction. This finding provides preliminary evidence of a retroactive uncertainty reduction reaction (Berger & Calabrese, 1975) when interacting with social robots, and with artificial agents in general. To explain our own and others' behaviour after an interaction takes place, we analyse and self- explain the situation. Once required to recall our own actions retroactively, we often become more prone to cognitive biases and lose objectivity to cues that are easier to explain than self-behaviour (Kahneman & Tversky, 1972). As time passes from the stimuli and more information has been processed, people experience inconsistency with their memory regarding their behaviour (Schacter, 1999) and form a perception in line with their preconceptions (Mahoney, 1977). These, as the results suggest, could be the agents' visual features, or perceptions regarding the agents' experience and agency.

2.4.5 Differences in disclosures to artificial agents are manifested in the voice

People' disclosures differed in communication and speech patterns according to the agent they were talking to. This finding matters for a number of reasons. It provides evidence that disclosure extends beyond measurements of quantity and people's overall perceptions of disclosure quality. While differences in disclosure quantity and subjective perception were limited to differences between artificial agents, information gleaned from participants' voices sheds light on a more complicated mechanism. Moreover, while different topics of disclosure shaped the content participants spoke about, the agents' embodiment elicited different reactions that were manifest in participants' voices.

It is important to consider basic prosody features for evaluating patterns of communications, speech styles, and emotional expression from the voice (Frick, 1985; Weiss, 2019). These include essential features such as rhythm, intonation, stress, and tempo of speech, which are conveyed with changes in pitch, voice intensity, harmonicity, speech rate and pauses (Crystal & Quirk, 1964; Pittam, 2020; Weiss, 2019). While previous studies in HRI and social robotics have focused on evaluating interactions on specific distinct processed prosodic patterns (Weiss, 2019) in specific contexts (e.g., Akalin & Köse, 2018; Breazeal & Aryananda, 2002; Fischer, Niebuhr, Jensen, & Bodenhagen, 2019; Kim, Leyzberg, Tsui, & Scassellati, 2009; Robinson-Mosher & Scassellati, 2004; Skantze et al., 2013), the current findings suggest a standardized method for drawing explicit causal inferences in voice signal differences across different agents could be useful. Here, changes in voice signal values reflected basic differences in voice production that were driven by the three different agents studied here, and these can be further processed into prosodic patterns for evaluating specific speech styles. Moreover, the experimental design, the voice signal extraction instrument, and analytical model can be easily replicated and applied in different settings and across a variety of conditions. Thus, the results of the present study provide empirical insights to changes and variations of voice features according to agents' embodiment. Whereas processed prosodic features might provide explanations to certain distinct behaviours, raw voice signals can demonstrate variances on a macro level that can be applied to a variety of measures and be replicated efficiently across different settings, conditions, and populations.

These changes correspond to, and were likely triggered by, unique features of the agent's embodiment. For example, the results of the second and third experiments provide clear evidence for people's voice being higher when communicating with the humanoid robot. This could potentially be triggered by robot's child-like embodiment and high-pitched voice. Another interesting example from the second and third experiments illustrates that disclosures to a disembodied agent were more harmonious. This could be triggered by associating the agent with pragmatic functionalities to follow simple and well-known commands, rather than as a sentient conversation partner. Hence, embodiment does not seem to follow a linear trajectory, but rather, we see evidence for clear categories and sets of features. Different features of embodiment call for different variations of voice signals, different reactions, and different behaviours.

2.4.6 Limitations and future research

While the study provides valuable insights, it is important to acknowledge its limitations for a more nuanced interpretation. Firstly, the lack of detailed participant characteristics, including age, cultural background, and prior experience with social robots, limits our understanding of how these factors may influence self-disclosure patterns and attitudes towards different agents. Moreover, the controlled laboratory environment in which the study was conducted might not fully capture the intricacies of real-life interactions, potentially undermining the ecological validity of the findings. Furthermore, the study primarily focused on immediate self-disclosure during short interactions, but exploring the long-term effects of disclosing personal information to social robots would provide a more comprehensive understanding of their impact on psychological well-being over time.

Having only one exemplar per category in the study design could have both advantages and limitations. The limitation of having only one exemplar per category is that it may not fully capture the wide range of variations and individual differences that exist within each type of social agent. Different humanoid robots or disembodied conversational agents can vary in appearance, voice, behaviour, and other features. By including only a single exemplar, the study may overlook important nuances and potential differences that could exist between various agents within the same category. However, on the positive side, it allows for a clearer comparison between the different types of social agents. By using consistent and uniform examples within each category, it becomes easier to isolate and identify the effects attributed to the agents' embodiment and characteristics. Moreover, Including Nao as a representative humanoid social robot is particularly relevant since it is widely utilized in HRI research. Nao's popularity ensures its replicability and reflects the current state of the art (see Amirova, Rakhymbayeva, Yadollahi, Sandygulova, & Johal, 2021). Additionally, using multiple robots can be cost-prohibitive and accordingly limit the number of potential exemplars under each category. To obtain a more comprehensive understanding of the effects of different social agents on self-disclosure, future studies could consider including multiple exemplars within each category. This would provide a more representative sample and enable researchers to explore how variations within each type of agent might influence participants' disclosure patterns and perceptions. Additionally, investigating a broader range of exemplars could offer insights into potential design considerations for social robots and conversational agents in health interventions.

By addressing these limitations and expanding upon the study's scope, researchers can enhance the validity, generalizability, and practical implications of their findings in real-world settings.

2.5 Conclusions

Taken together, the results of this study highlight the complexity of extracting meaning from disclosures to social robots and artificial agents in general. Current behavioral (e.g., eye tracking and motion tracking), performance (e.g., reaction times, error rates) and physiological (e.g., heart rate, skin conductance, respiratory rate) measures often used in HRI research are prone to variety of challenges for participants as well as experimenters, such as discomfort, disruptions, and low temporal resolution (Wiese et al., 2017). Here we attempted to address how voice signals can be used as natural behavioural and performance measures in empirical research, and also as physiological measures (Giddens et al., 2013; Ruiz et al., 1990; Slavich et al., 2019; van Puyvelde et al., 2018). Furthermore, as was demonstrated in this study, lexical and content features can be extracted from audio data to provide meaningful insights regarding a disclosure's' volume and essence (Kreiner & Levi-Belz, 2019; Tausczik & Pennebaker, 2010; Weiss, 2019). Self-reported measurements provide access to one's subjective perceptions to their disclosure to others, and hold value for expanding on the cognitive connection between perception and speech (J. O. Greene, 1984, 1995). Voice signals, content and lexical features, together with self-reported measurements, offer a comprehensive set of measures with which to evaluate disclosure to social robots for assessing interactions. Finally, following Kreiner and Levi-Belz (2019) suggestions, by employing a multidimensional approach, this study stresses the complicated nature of self-disclosure, where a single measure cannot capture its complexity and nuance.

These results hold several implications for assessing interactions with socially assistive robots, and for human-robot interaction research in general. As researchers and engineers work to develop social robots, agents, and software that rely upon high quality verbal input from human users, these developers would be well served to consider the stimulus cues to agent embodiment that will lead to optimal eliciting of information from human users. Since different cues to embodiment call for different patterns of communication, it is important to identify the communicative requirements for the task or agent at hand. Furthermore, the current results highlight the fact that assessing quality of interactions in disclosures, especially in assistive settings, is not purely a matter of the quantity of information.

Chapter 3

Human–Robot Relationship: Long-Term Effects on Disclosure, Perception and Well-Being

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A preliminary version of this chapter was accepted for publication and presentation at *ACM International Conference on Human–Agent Interaction 2022* under the title: "User experience of human-robot long-term interactions" (see Laban, Kappas, Morrison, & Cross, 2022b), and a full version of this chapter was submitted for publication in *International Journal of Social Robotics* on 16/12/2022 (see Laban, Kappas, et al., 2022a).

Abstract

Since interactions with social robots are novel and exciting for many people, one concern is the extent to which people's behavioural and emotional engagement with robots might develop from initial interactions with a robot, when a robot's novelty is especially salient, and sustained over time. This challenge is particularly noticeable in interactions designed to support people's well-being, with limited evidence for how social robots can support people's emotional health over time. Accordingly, this research is aimed at studying how long-term repeated interactions with a social robot affect people's self-disclosure behaviour toward the robot, perceptions of the robot, and how it affected factors related to well-being. We conducted a mediated long-term online experiment with participants conversing with the social robot Pepper 10 times over 5 weeks. We found that people self-disclose increasingly more to a social robot over time, and found the robot to be more social and competent over time. Participants' moods got better after talking to the robot and across sessions, they found the robot's responses to be more comforting over time, and they also reported feeling less lonely over time. Finally, our results stress that when the discussion theme was supposedly more emotional, participants felt lonelier and stressed. These results set the stage for addressing social robots as conversational partners and provide crucial evidence for their potential introduction as interventions supporting people's emotional health through encouraging self-disclosure.

3.1 Introduction

Social robots have been shown to effectively elicit socially meaningful behaviours and emotions from humans across a number of experimental and real-world contexts (Henschel et al., 2021; Hortensius et al., 2018; Laban, George, et al., 2021). Nevertheless, one of the challenges to human–robot interaction (HRI) research is employing and evaluating long-term interactions, especially in people's natural settings. Since interactions with social robots are novel and exciting for many people, one particular concern in this specific area of HRI is the extent to which behavioural and emotional expressions might develop from initial interactions with a robot, when its novelty is particularly salient, to responses, behaviours, and perceptions that are sustained over time (Smedegaard, 2019, 2022). Empirical studies in this area of HRI research are often limited to controlled laboratory settings, due to various logistical (e.g., limited number of robots per lab and robots' high cost) and technical factors (e.g., multiple computers or other controlling devices required to coordinate a robot's behaviours and/or requirements for skilled Wizard-of-Oz (WoZ) operation). These challenges can make it difficult for HRI researchers to gain insights into factors that shape people's long-term interactions with social robots in natural, real-world settings. This is especially noticeable with studies that are focused on evaluating the use and utility of social robots in social settings. Robots for these settings are often designed to interact and communicate with humans or other agents (such as pets or other robots) by following social scripts and rules relevant to their role and function within social settings (Breazeal, 2003; Henschel et al., 2021). Our understanding of social robots' potential scope and limitations will be substantially informed by devising experiments where people can interact for a period of time with robots in natural social settings, such as at one's home, workplace, local clinic, or school.

This particular challenge is noticeable in interactions designed to support people's well-being. Social robots are widely studied and are gradually being applied in care settings, aimed at supporting people's physical and mental well-being (Henschel et al., 2021). However, due to the complexity of administering social robotic interventions, studies in the field rarely establish ecologically valid interactions with human users, using insufficient methods (e.g., using single-subject studies, quasi-experimental designs, cross-sectional research designs, etc.), and employ studies with single interactions rather than ongoing longitudinal interventions (see N. L. Robinson et al., 2019).

Considering social robots' social features (Cross & Ramsey, 2021; Hortensius & Cross, 2018), animated design (Cross et al., 2016; Hortensius et al., 2018), and autonomous abilities (Henschel et al., 2021), social robots could support monitoring people's health, as well as improve their emotional well-being by engaging in self-disclosure in people's natural settings. Self-disclosure is a communication behaviour aimed at introducing and revealing oneself to others, and it plays a key role in building relationships between two individuals (Jourard & Lasakow, 1958; Pearce & Sharp, 1973). It serves an evolutionary function of strengthening interpersonal relationships, while also producing a wide variety of health benefits, including helping people to cope with stress and traumatic events through eliciting help and support (Frattaroli, 2006; Frisina et al., 2004; Kennedy-Moore & Watson, 2001). Moreover, self-disclosure appears to play a critical role in successful treatment outcomes (Sloan, 2010) and has a positive impact on mental and physical health (Derlega et al., 1993). For health interventions to succeed, they depend on open channels of communication where individuals can disclose needs and emotions, from which a listener can identify stressors and respond accordingly (Colquhoun et al., 2017; Wight et al., 2016). This is crucial for interventions with social robots, as human behaviour and emotions are analysed and synthesized by machines from human output, to respond and react appropriately (Kappas et al., 2020).

Given the necessity of studying social robotic interventions in a long-term manner, as well as the importance of self-disclosure for psychological health and HRI, this study is aimed at evaluating people's self-disclosure interactions with a social robot over time. More specifically, we would like to study how prolonged and intensive interactions with a social robot affect people's self-disclosure behaviour toward the robot, perceptions of the robot, and how it affected factors related to well-being. Therefore, we were asking –

RQ1: To what extent people's self-disclosures, perceptions of the robot, as well as well-being, are affected over time in long-term interactions with a social robot?

To have a further understanding of the application of social robots in different emotional settings, we were also interested in the role of the interaction's discussion theme. Hence, we were also asking –

RQ2: To what extent people's self-disclosures, perceptions of the robot, as well as well-being, are affected due to the discussion theme in long-term interactions with a social robot?

To answer our research questions we conducted a mediated long-term online experiment with participants conversing with a social robot 10 times over 5 weeks about general everyday topics. Participants were allocated to two groups, discussing topics framed to the Covid-19 pandemic, or the same topic except the discussion had no explicit mention of the Covid-19 pandemic.

3.2 Related work

The mere-exposure effect refers to the psychological phenomenon where people develop a preference for things they are repeatedly exposed to (Zajonc, 2001). In the context of long-term HRI, the mere-exposure effect operates differently compared to the realm of Human–Computer Interaction (HCI) focusing on usability. In HCIs, users often acquire a positive attitude towards tools and objects through repeated use and familiarity, leading to improved usability (Van Giesen, Fischer, Van Dijk, & Van Trijp, 2015). However, in the domain of HRI, where social interaction with robots is a key component (Henschel et al., 2021), the dynamics change. The social dynamic in HRI sets it apart from traditional HCI. Unlike HCI, where the focus is primarily on optimizing usability and functionality (Van Giesen et al., 2015; Issa & Isaias, 2015), HRI incorporates a social component, aiming to create a sense of companionship or collaboration. Robots are designed to engage with humans in a more social manner, simulating human-like behaviours, gestures, and communication. This social element introduces a unique dynamic, where humans naturally seek to establish social connections, rapport, and even attribute human-like qualities to the robots (Henschel et al., 2021). The social dynamics in HRI require a deeper understanding of human–robot communication beyond usability, and instead focus on the development of a social bond between humans and robots.

Longitudinal designs are important for understanding people's long-term adaptation of social robots, and moreover, to further understand human behaviour and perception of social robots and how it changes over time (Leite et al., 2013). While single interaction studies provide us with interesting insights into human behaviour when engaging with robots, we are often challenged to learn from these studies as "in the wild" application of robots aims to develop machines that people interact with over sustained periods of time (Henschel et al., 2021; Sabanovic, Michalowski, & Simmons, 2006). One of the most significant (and common) limitations to one-off HRI studies relates to novelty effects (see Smedegaard, 2019, 2022), while long-term studies have often found evidence for reduced engagement with various robotic platforms over time (Dautenhahn, 2007; Leite et al., 2013). As social robots are a new emerging technology that is still novel and exciting for most, users often have high expectations for social robots and experience dissonance when a social robot's performance fails to meet their expectations. Accordingly, when users interact with robots over time, they tend to perceive them as being less social as interactions go on as their expectations of the robot are not being fulfilled (Smedegaard, 2022). Previous studies show that even household robotic devices that are not particularly social (like the Roomba vacuum cleaner) suffer from the novelty effect (Sung et al., 2009), with users being excited about the robotic device at first and using it less as they get familiar with it.

Due to the constrained and highly choreographed nature of many HRI studies, deep insights into people's responses and interactions with robots in natural settings remain relatively rare. Of the field studies that have conducted HRI research in these spaces, important insights are emerging from both single interaction (e.g., Stower & Kappas, 2020; Holthaus & Wachsmuth, 2021) and repeated interaction (e.g., Céspedes, Irfan, et al., 2021; De Graaf, Allouch, & Klamer, 2015; De Graaf, Allouch, & van Dijk, 2016; Feingold Polak & Tzedek, 2020; Levinson et al., 2020; van Maris et al., 2020; Jeong et al., 2022) studies, with much of this work taking place in public spaces or tied to specific settings like education (e.g., Kanda, Hirano, Eaton, & Ishiguro, 2004; Levinson et al., 2020; Michaelis & Mutlu, 2017, 2019; Woo, LeTendre, Pham-Shouse, & Xiong, 2021; N. L. Robinson, Ward, & Kavanagh, 2021), care (e.g., N. L. Robinson et al., 2020b, 2020a; Nomura, Kanda, Yamada, & Suzuki, 2021; van Maris et al., 2020; Bodala et al., 2021; Jeong et al., 2022), or rehabilitation (e.g., Céspedes, Irfan, et al., 2021; Céspedes, Raigoso, Múnera, & Cifuentes, 2021; Feingold Polak & Tzedek, 2020; Koren, Feingold Polak, & Levy-Tzedek, 2022; Feingold-Polak et al., 2021; Afyouni et al., 2022). Longitudinal studies that address similar questions with disembodied agents such as virtual assistants and chatbots (e.g., Croes & Antheunis, 2020, 2021; Ho et al., 2018) benefit from access to users' personal devices, whereas research with physically embodied artificial agents (i.e., social robots) remains far rarer due to challenges with logistical and cost barriers to situating these devices in users' domestic settings (i.e., in their home environment) to explore single or repeated interactions. While several attempts have been made before to reduce the barriers to feasibility for such work (c.f., Hortensius, Chaudhury, Hoffmann, & Cross, 2022; Cross, Riddoch, et al., 2019; De Graaf et al., 2015, 2016; Jeong et al., 2022), we still know relatively little about user perceptions of and behaviours toward social robots when these take place in familiar home environments. Further insights into the challenges and opportunities afforded by placing social robots into familiar domestic settings should aid human-robot communication in general, as well as further refine the development and utility of these machines for commercial use.

3.2.1 Social Robots for Well being

Social robots hold great potential for delivering or improving psycho-social interventions (N. L. Robinson et al., 2019), supporting mental health (Scoglio et al., 2019), monitoring symptoms of chronic psychopathologies (Laban, Ben-Zion, &

Cross, 2022), aiding rehabilitation (Feingold Polak & Tzedek, 2020) and providing much-needed physical and social support across a number of daily life settings (Henschel et al., 2021). For example, a previous study by Nomura et al. (2020) showed the benefits of employing social robots for minimising social tensions and anxieties, describing that participants with higher social anxiety tended to feel less anxious and demonstrate lower tensions when knowing that they would interact with robots in opposition to humans. In fact, a recent paper by Rasouli, Gupta, et al. (2022) stresses the benefits of employing social robots as interventions for social anxiety, stating that these could complement the support provided by clinicians. The authors explain that social robots could support people to get into therapy and maximize the effectiveness of the therapy by increasing the patients' engagement and continuing the support outside the therapy session. In a previous paper (Laban, Ben-Zion, & Cross, 2022) we addressed similar benefits of using social robots for diagnosing and treating people suffering from post-traumatic stress disorder (PTSD), social robots can assist with overcoming several logistical and social barriers that trauma survivors face when required to monitor symptoms and when seeking mental health interventions.

Beyond supporting people who are suffering from clinically diagnosed psychopathologies like PTSD and anxiety, social robots could also provide emotional support via self-managed interventions to healthy individuals that might experience difficult emotional situations and stressors in their daily lives. Previous studies administered the application of social robots in emotionally supportive settings showing meaningful outcomes in terms of cognitive change and affect. A study by Bodala et al. (2021) employed a social robot delivering teleoperated mindfulness coaching for five weeks. Another example by M. Axelsson et al. (2022) tested a robotic coach conducting positive psychology exercises, showing positive mood change after participation in the robotic intervention. Robotic interventions for people's well-being are rarely taking place in people's homes. One successful example is a study employing the social robot Jibo as a positive psychology coach to improve students' psychological well-being in students' on-campus housing. The study results describe a positive effect on students' psychological well-being with positive mood change, and also students expressing their motivation to change their psychological well being (Jeong et al., 2022). Other studies show positive outcomes in terms of behavioural change. A series of studies by Robinson and colleagues used social robots to deliver behaviour change interventions, applying verbal motivational interventions for reducing high-calorie snack consumption. The studies showed promising results addressing the behavioural change using objective measurements like weight loss (N. L. Robinson et al., 2020a), and also via qualitative data addressing the subjective experiences of the participants during such interventions (N. L. Robinson & Kavanagh, 2021). A similar intervention have been tested with a clinical population showing potential for using social robots for diabetes management (N. L. Robinson et al., 2020b).

The recent COVID-19 pandemic further illuminated the potential of social robots as an assistive technology in times when strict infection control measures mandate physical distancing between people. Several researchers have argued that physically embodied social robots should be able to assist with a number of tasks to help keep people physically and mentally healthy, ranging from temperature taking and food and supply delivery to providing companionship for individuals suffering from loneliness (Scassellati & Vázquez, 2020; Henschel et al., 2021; Henschel & Cross, 2020; G.-Z. Yang et al., 2020; Gasteiger, Loveys, Law, & Broadbent, 2021), and even mediating social interactions with other individuals (Isabet, Pino, Lewis, Benveniste, & Rigaud, 2021). Nevertheless, as discussions concerning the potential applications for social robots became more prominent during the pandemic, HRI research was limited due to social distancing and the inability to use lab facilities for research that is highly dependent on laboratory-constrained environments. The pandemic forced most individuals (including researchers) to adopt computer-mediated means of communication (CMC) (Choi & Choung, 2021). Following the wholesale adaptation to CMC during the pandemic, the current research sets forth a means for conducting rigorous and reproducible social robotics research to explore people's engagement with social robot-mediated interactions within their own homes. More generally, this research sets the stage for further research exploring online mediated speech-based psychosocial interventions with social robots when public health, cost, or logistical barriers prevent situating a physically embodied robot in users' homes across the long term.

3.2.2 Self-disclosing to robots and artificial agents

Several studies address self-disclosure to social robots in single sessions (e.g., Laban, George, et al., 2021; Shiomi et al., 2020; Duan et al., 2021; Hoffman et al., 2014; Nakamura & Umemuro, 2022; De Groot et al., 2019), however, there is limited literature of studies that address self-disclosures to robots in long-term settings with limited findings (e.g., van Wingerden et al., 2020). Previous studies describe that in single interactions people's subjective perceptions of their self-disclosures to robots tend to align objectively well with their actual disclosures. Moreover, people tend to share more information with humans than with humanoid social robots or other artificial agents (Laban, George, et al., 2021). Yet, a different study by Nomura et al. (2020) found that speech interactions with a social robot elicited lower tensions compared to interactions with a human agent. Another recent study explains that people might self-disclose more to a robot when conversing with a robot that changes their listening attitude (Nakamura & Umemuro, 2022). Long-term studies with disembodied conversational agents give us some evidence of the nature of long-term self-disclosure to artificial agents. For example, a longitudinal study byCroes and Antheunis (2020) tested long-term interactions with the chatbot Mitsuku via 7 interactions that were conducted over 3 weeks. Their results show that social processes decreased after each interaction with Mitsuku and that participants reported lower feelings of friendship with Mitsuku across sessions. They describe the presence of the novelty effect, with participants describing how Mitsuku became predictable after the first session. An additional study by Croes and Antheunis (2021) showed that in self-disclosure interactions despite feeling more anonymous when interacting with chatbots, people trust humans more than they trust chatbots and reported for higher degrees of social presence.

3.2.3 Using self-disclosure for social robotic intervention

The literature describes that various forms of human-human self-disclosure can support and improve mood and provide a convenient space for concealment and regulating emotions with many health benefits. For example, James Pennebaker writing disclosure paradigm (Pennebaker, 1997; Pennebaker & Beall, 1986) helps people to facilitate their emotions when writing about their own experiences. Interestingly, previous studies found that people in bad mood benefited more from disclosing to a robot than participating in writing disclosure using a journal (Duan et al., 2021) or on social media (Luo et al., 2022). Another good example is affect labelling, a simple and implicit emotional regulation technique aimed at explicitly expressing emotions, or in other words - putting feelings into words (Torre & Lieberman, 2018). In addition, the act of self-disclosure is highly useful for emotional introspective process, self-reflection on one's emotions, actions, and behaviours (Tamir & Mitchell, 2012), and is a meaningful act of mindfulness (Creswell et al., 2007). In the previous section, we mentioned several studies applying social robots in emotionally supportive settings (see Bodala et al., 2021; M. Axelsson et al., 2022; Jeong et al., 2022), but social robotic interventions rarely encourage open self-disclosure. Considering the vast evidence for the positive effect of self-disclosure on emotional well-being, our behavioural paradigm was aimed at encouraging participants to self-disclose to a social robot as a therapeutic activity. Engaging a robot in a reciprocal conversational interaction is a complex technical task, that might negatively affect people's disclosures and perceptions of the robot and the interaction due to the robot's communication limitations. However, here we suggest that employing a social robot for encouraging and listening to people's disclosure (an act that would not be as limiting to the robot's communication skills) would have a positive effect on people's disclosures and perceptions. Furthermore, we suspect that by engaging people in self-disclosures to a social robot, participants would be engaged in affect labelling (Torre & Lieberman, 2018) and it will positively affect their well-being.

3.3 Methods

Consistent with recent proposals (Nelson et al., 2012; Simmons et al., 2011), we pre-registered the study and report for how we determined our sample size, all data exclusions, all manipulations and all measures in the study (see Laban, Kappas, Morrison, & Cross, 2021b). In addition, following open science initiatives (e.g., Munafò et al., 2017), the de-identified data set, stimuli and analysis code associated with this study are freely available online (Laban, Kappas, Morrison, & Cross, 2020). By making the data available, we enable and encourage others to pursue tests of alternative hypotheses, as well as more exploratory analyses. Preliminary results were presented as a poster at the 10th edition (2022) International Conference of Human–Agent Interaction (see Laban, Kappas, et al., 2022b).

3.3.1 Experimental Design

A between-groups 2 (Discussion Theme: Covid-19 related or general) by 10 (chat sessions across time) repeated measures experimental design was followed. Participants were randomly assigned to one of the two discussion topic groups, according to which they conversed with the robot Pepper (SoftBank Robotics) via Zoom video chats about general everyday topics (e.g., social relationships, work-life balance, health and well-being; see Table 3.1) for 10 sessions. One group's conversation topics were framed within the context of the Covid-19 pandemic (e.g., social relationships during the pandemic, sustaining mental health during the pandemic, etc.), whereas the other group's conversation topics were similar, except no explicit mention of the Covid-19 pandemic was ever made (see Section 3.3.4). Each interaction consisted of the robot asking the participant 3 questions (x3 repetitions). The topic of each interaction was assigned randomly before the experimental procedure started, as was the order of the questions. Participants were scheduled to interact with the robot twice a week during prearranged times for five weeks.

3.3.2 Participants

Sample

A priori power calculations using G*power software (Faul, Erdfelder, Lang, & Buchner, 2007; Faul, Erdfelder, Buchner, & Lang, 2009) suggest that for reasonable power (0.83) to detect small to medium effect sizes, a sample size of 22 participants would be required. Due to the relatively complex data collection procedure and the potential for a high dropout rate, we recruited 40 participants via the Prolific website. One participant dropped out, resulting in a final sample size of 39 participants. Participants were between the ages of 18 and 60 (M = 36.41, SD = 12.20), 54% identify as females, and the rest identify as males. More than half (59%) of the sample reports having a Bachelor's degree as their highest level of education, and more than half of the sample (51.3%) are employed full-time. 55% of the sample are either married (33.3%) or in a relationship (21.7%). 41% of the sample have at least one child. Most of the participants (97.4%) did not live on their own during their participation in the study, with an average number of 3.36 individuals (SD = 1.37) in a household (including the participant). Almost all of the participants (92%) did not have previous experience with robots.

Target Population

The target population for this study was exclusively adults from the general population aged 18 or over with normal to corrected to normal vision, no known mental disability, hearing loss or difficulties, or physical handicap, native English speaking, and currently residing in Great Britain. Due to the technical requirements of the mediated experimental design, the target population of this study consisted of individuals with access to a personal computer with Zoom installed, a functioning web camera, a stable internet connection, a microphone, and speakers/headphones.

Recruitment

Participants were recruited via Prolific and were allowed to participate only after confirming that they were older than 18 years, are native English speakers, and have access to a computer with Zoom installed as well as a decent web camera, stable internet connection, microphone, and speakers/headphones. Also, Prolific users were asked to commit to attending 2 sessions a week across 5 weeks. Eligible Prolific users could access the Prolific page of the study to receive further information, consider their participation, and complete the induction questionnaire if interested. On the Prolific page of the study (of the induction questionnaire - Session 0) and in the induction questionnaire Qualtrics form, Prolific users were introduced to the study, the task, and the available time slots as part of the longitudinal experiment schedule. After receiving this information about the study's requirements, Prolific users were then asked if they would like to continue in the study by declaring that they can commit to the study's requirements. Finally, Prolific users were then asked to choose their participation time slots, after which they received a participant number to start their participation. Participants were paid a total of £3 for every 30 minutes of participation or participation session if it lasted less than 30 minutes. Participants who completed all 10 sessions were paid an extra £20 after their final interaction. A detailed description of the recruitment procedure and a full list with specific Prolific filters used for participant recruitment can be found in the study's OSF page (see Laban, Kappas, et al., 2020).

Ethics and Communication

All study procedures were approved by the research ethics committee of the University of Glasgow (ethics approval numbers 300200094 & 300200132). All participants provided written informed consent before participating in the study. Participants were asked to provide, if they wished, optional consent to allow the research team to use their video and audio footage (including videos, audio, and photos made from video material) as materials for research publications, conference presentations, and other multimedia outputs that can and might be disseminated and distributed online, in the media and for public presentations. All Prolific users interested in participating in the study were introduced to the study, the requirements of the study, and the task, but were not informed about the functionalities of the robot Pepper, to ensure all robot knowledge or priming was minimised. During each session (including Session 0), participants were re-introduced to the study, the study's schedule (about their chosen day of participation), and received reminders and information about what the study involves. Furthermore, they were reminded about the benefits and risks of their participation (i.e., ensuring that they would receive their payment, no risks were anticipated as a result of study involvement, and their right to withdraw their participation at any time with no penalty or punishment). Participants were further informed how their data (i.e., behavioural and self-reported data collected in the study) would be used and again reminded of their right to withdraw their data and/or ask that it not be used at any time during or after their participation. Participants were guaranteed that their right to privacy and anonymity would be respected and that no identifiable data would be shared with anyone beyond the research team. Participants were reminded that their participation was voluntary and they were given the contact information of the main researcher and experimenter should they wish to follow up with any further questions. After completing the study, participants received a comprehensive debriefing message in Prolific (forwarded by Prolific to their associated email address), providing further information about the study, the deception that was used (i.e., the experimenter was using WoZ approach for communicating with participants to make it look like the robot was responding autonomously), and were again given the contact information of the main researcher and experimenter should they wish to follow up with any further questions or feedback.

When completing each session, participants were reminded in the Qualtrics form about the date of their next session. Two days before each session, participants received an email via Prolific regarding the specifics of their next session. This message contained details about the session number, the time at which the Prolific page with the link for the session questionnaire form would be published, a reminder not to start the session before the allocated participation time slot, and to contact the experimenter if they are to be late, cannot remember their participation time-slot, or cannot make it. Finally, participants were thanked for their participation and cooperation in each of these messages and were reminded of their rights and the fact that they were welcome to contact the experimenter at any time using the Prolific messaging system, or by email. On the day of participation, participants received an automated message from Prolific at 08:00 AM, that the Prolific page of the session is available online. Later that day, 30 to 15 minutes before each participant's participation time slot, each participant received an individual message via Prolific from the experimenter about their upcoming session and where they could find the link to start the session. If and when participants were late to their participation (without providing earlier notice that this would be the case), the experimenter messaged the participant via Prolific to ensure attendance or reschedule the session. When participants experienced any technical difficulties or needed to communicate with the experimenter, they were instructed to do this via Prolific or email, and not using the Zoom chat. This was to reduce any potential association between the session interactions with the robot and the experimenter. Accordingly, all communications between participants and the experimenter took place via the Prolific messaging centre or emails on rare occasions (when initiated by a participant). The main researcher and experimenter (GL) signed his name on all communications with participants.

3.3.3 Stimuli

Conversational interactions were guided by the robot Pepper (SoftBank Robotics), a humanoid robot capable of communicating via speech and gestures. Following Leite et al. (2013) guidelines for social robots' design for long-term interactions,

Figure 3.1: The lab settings, including the robot Pepper (SoftBank Robotics) in front of a web camera, while the experimenter in the back is controlling the robot using the Wizard of Oz technique.

Pepper was chosen as a suitable robotic platform for this task, given the alignment between Pepper's humanoid embodiment and the social requirements of the conversational task (see Leite et al., 2013, "Guidelines for Future Design"). While Pepper's appearance and behaviours are somewhat human-like (i.e., Pepper has a head, face, torso, two arms, two hands, five fingers per hand, etc.), Pepper has not been designed to resemble a real person. Instead, Pepper's embodiment and behaviours clearly convey human likeness, (further evidenced, for example, by Pepper's abilities to communicate using human speech, but not demonstrating any facial expressions given the rigid, immobile face and head).

Pepper was placed in front of a web camera (Logi-tech, 1080p), connected to the experimenter's computer (see Figure 4.1). Behind Pepper was a white wall and a flowerpot with a green plant (see Figure 4.2). Pepper communicated with participants in this study via the WoZ technique controlled by the experimenter via a PC laptop. All pre-scripted questions and speech items were written and coded in the WoZ system, with the experimenter controlling Pepper by pressing buttons on a PC laptop. Accordingly, the procedure followed a clear pre-programmed protocol where the experimenter did not need to speak or type anything during the interaction, but only pressed the relevant keys to trigger the required or appropriate text delivery via Pepper.

Pepper responded to participants' answers and statements with neutral or empathetic responses. Pepper's vocabulary was limited and constrained to reflect the current state of speech recognition technology in social robotics. Following Leite et al. (2013) guidelines for social robots' design for long-term interactions, Pepper's responses were affective and empathetic, aiming to convey an understanding of users' affective state, communicate appropriate responses, and also display contextualised affective reactions (see Leite et al., 2013, "Guidelines for Future Design"). Hence, a limited set of responses were pre-defined for answers and statements with neutral sentiment or containing factual information (e.g., "I understand", "I see", "okay"), for answers and statements of positive sentiment (e.g., "I am happy to hear that", "This is really interesting", "That's amazing"), and for answers and statements of negative sentiment (e.g., "I am sorry to hear that", "This sounds very challenging", "These are not easy times"). Moreover, Pepper had pre-defined statements for opening an interaction (e.g., "Hello there", "Hi!", "How are you doing today?"), closing an interaction ("That's it for now", "See you next time", "Have a good weekend", "Goodbye"), answer with basic polite gratitude (e.g., "I am fine, thank you!", "Thank you", "That is lovely of you to say so", "It was nice to chat with you too!"), and thank participants for their cooperation and disclosures (e.g., "Thank you for sharing with me", "Thank you for telling me", "What a nice memory. Thank you for sharing with me"). Due to Pepper's high-pitched voice and robotic style of pronunciation, Pepper's answers and statements were structured using commas so that Pepper's speech segments will be clearer. See the OSF repository (Laban, Kappas, et al., 2020) for a file with all of Pepper's vocabulary and the structure of Pepper's speech segments.

Pepper communicated using a cheerful, high-pitched voice, and expressive and animated body language that corresponded to the spoken content and Pepper's physical capabilities. Pepper's movements were self-initiated based on Pepper's demo software's "animation" function, in order to provide a sense of neutral interaction and to ensure replicability by future studies using the same functionality that all Pepper robots are equipped with. Moreover, Pepper's gaze was almost always focused on the camera, but it shifted and moved from the camera with no pre-programmed logic. To ensure that the mediated interactions would come across as natural, Pepper's gaze was not programmed to be focused on the camera at all times as this would not be normal behaviour with conversing with a human interlocutor. Therefore, Pepper's gaze shifts were allowed to naturally occur following its demo software.

3.3.4 Manipulation

In accordance with Leite et al. (2013) guidelines for social robots' design for long-term interactions, the interactions followed a clear structure and routine, including greetings and farewells, identifying participants by their name, and demonstrating appropriate affective and emphatic responses to participants' answers to provide a sense of personal interactions and encourage self-disclosure (see Leite et al., 2013, "Guidelines for Future Design").

Structure

Each interaction was guided by Pepper as a semi-structured interview discussing non-sensitive topics regarding general everyday experiences. Each interaction followed the same order, starting with greetings followed by 3 questions (x3 repetitions). The participants were instructed to have a short conversation with Pepper, following Pepper's lead in the interaction and answering Pepper's questions. Participants were instructed that no time limit was applied for the interactions and that the interactions usually took about five to ten minutes. They were further encouraged to participate in the interactions the way they saw fit - speaking as little or as much as they wished. In addition, participants were instructed that there were no correct or incorrect answers, and they were encouraged to provide honest answers according to what they felt comfortable with. In the first interaction with Pepper (Session 1), participants were asked for their name by the robot as part of the robot introduction (i.e., "Hello there, my name is Pepper, what is your name?), as such a question would be part of a normal introduction in on-going social exchanges with another person. Before the interaction started, participants were instructed that they were not obliged to share their names with the robot and that they could give a fake name if they preferred to do so. From the second interaction (Session 2) onwards, Pepper addressed each participant by the name they gave during the first interaction (Session 1), to provide a sense of natural and personalized interactions. The task followed the following structure and order:

- Short greetings/introduction (e.g., Hi there, how are you doing?).
- One pre-defined general question about the participant's day, week, or weekend, to build rapport (e.g., "how was your weekend? Did you do anything interesting?").
- An opening statement introducing the topic of the question (e.g., "I am about to ask you about your social life").
- Two pre-defined, non-sensitive questions that correspond to the topic that was randomly allocated to the interaction. These questions were either framed in the context of the COVID-19 pandemic or in a more general everyday context, depending on the discussion theme group assignment.

Content

Previous studies that investigated relationship formation and disclosure with artificial agents followed conceptual frameworks for inducing rich disclosures and forming meaningful connections (e.g., Croes & Antheunis, 2020, 2021; Laban, George, et al., 2021; Riddoch & Cross, 2021). For example, a study by Croes and Antheunis (2021) presented an implementation of 36 questions as a method to generate interpersonal closeness (see Aron et al., 1997, "36 questions to love") and elicit self-disclosure from human users to a chatbot. A previous study from our group (Laban, George, et al., 2021) demonstrated how simple questions about everyday experiences (i.e., work-life balance and finances, social life and relationships, and health and well-being) can elicit meaningful disclosures when communicated by a social robot. The questions and topics in the study were influenced by Jourard and Lasakow (1958) and Jourard (1971) as an elicitation technique aiming to capture participants' subjective experiences regarding various everyday topics. Here we used a similar type of questions to the ones used in Laban, George, et al. (2021), adapting disclosure topics for the ten sessions from Jourard (1971) and Connell et al. (2012), and framing the disclosure topics and questions in this study following a framework and guidelines by Connell et al. (2012).

	Topic	Category
1	Work	Control, Autonomy, and Choice
2	Leisure and Passions (Life)	All
3	Finances	Control, Autonomy, and Choice
4	Relationships	Belonging
5	Social life	Belonging
6	Mental Health	Well-being and Ill-being
7	Physical Health	Well-being and Ill-being
8	Personality	Self-Perception
9	Goals and Ambitions	Hope and Hopelessness
10	Routine and Daily Activities	Activity

Table 3.1: The ten topics and corresponding quality of life categories following Connell et al. (2012) framework.

The framework by Connell et al. (2012) introduces guidelines via six main themes for asking questions that capture and elicit disclosures that relate to different elements of quality of life within counselling psychology settings and mental health therapy. The guidelines and themes were defined by Connell et al. (2012) after reviewing and synthesizing qualitative research studies (especially from the counselling psychology literature, psychotherapy, and mental health therapy literature) that explicitly asked adult participants with mental health problems about the factors they considered important to their quality of life or how it had been impacted by their mental health. Based on Connell et al. (2012) review's results the six themes are: (1) Well-being and Ill-being, (2) Control, Autonomy, and Choice, (3) Self-Perception, (4) Belonging, (5) Activity, (6) Hope and Hopelessness.

The ten topics for the ten sessions describe one or more of the six themes described by Connell et al. (2012), aiming to elicit meaningful disclosures following Jourard (1971) guidelines, but also to initiate self-reflection and capture meaningful information regarding the quality of life and mental health, following Connell et al. (2012) framework. The ten topics and their corresponding themes according to Connell et al. (2012) framework can be seen in table 3.1. The phrasing of each of the two questions under each topic followed Aron et al. (1997) approach for questions and practical methodology for creating interpersonal closeness in an experimental context. See the questions in the OSF repository (Laban, Kappas, et al., 2020).

Discussion Themes

For both discussion themes, the interaction always started the same way, with greetings and with the robot asking the first question about the participant's day/week/weekend (see section 3.3.4 for the structure of the task). The following two pre-defined questions were about a topic that was randomly allocated to the interaction from the 10 topics about general everyday experiences (see table 3.1). For participants assigned to the neutral discussion theme group, the questions were not limited to any specific frame other than general everyday context. For participants assigned to the Covid-related discussion theme group, questions were asked about the same topics, however, the questions were framed within the context of the COVID-19 pandemic. For example, participants were asked how their work situation changed due to the pandemic, or how they were socializing during the pandemic. See the questions and differences between conditions at the OSF repository (Laban, Kappas, et al., 2020).

The separation based on the discussion theme was chosen because COVID-19 was a significant and globally prevalent event at the time of conducting the study. It had a substantial impact on people's lives, emotions, and well-being. By comparing the two groups, one discussing pandemic-related topics and the other discussing the same matters yet with no explicit mention to the pandemic, we could examine the influence of a specific emotionally charged theme (COVID-19) on participants' engagement and well-being during their interactions with the social robot. Additionally, by including a group discussing non-pandemic-related issues, we could establish a baseline for comparison. This allowed us to determine if any changes in self-disclosure, perceptions of the robot, and well-being were specifically attributed to the emotional content of the discussion theme (COVID-

19) or if they were more generally influenced by the repeated interactions with the robot.

3.3.5 Measurements

To ensure that our models only include high-quality data, we included only cases that were captured and processed correctly.

Demographics

Participants were requested to complete a short questionnaire that gathered information on demographic parameters including age, biological sex, gender identification, level of education, nationality, job, previous experience with robots, and whether English is their native language.

Disclosure

Subjective self-disclosure Participants were requested to report their level of subjective self-disclosure via the sub-scale of work and studies disclosure in Jourard's Self-Disclosure Questionnaire (1971). This questionnaire was adapted and adjusted for the context of the study, addressing the statements to general life experiences. The measurement included ten self-reported items for which participants reported the extent to which they disclosed information to Pepper on a scale of one (not at all) to seven (to a great extent). Accordingly, a mean scale was constructed ($M = 3.60$, $SD = 1.17$) which was found to be reliable (Cronbach's $\alpha = .83$).

Disclosure duration Duration of speech in seconds from each recording was extracted and processed using Parselmouth (Jadoul et al., 2018), a Python library for Praat (Boersma & Weenink, 2001).

Disclosure length The volume of disclosure in terms of the number of words per disclosure. The recordings were automatically processed using the IBM Watson speech recognition engine, applying the British telephony model. To ensure capturing all utterances within each disclosure we amplified the audio files with 7 decibels and slowed the audio file's pitch. The number of words per disclosure was extracted from the text using a simple length command in Python.

Disclosure compound sentiment Using Vader for Python (Hutto & Gilbert, 2014), the disclosures were measured to determine their overall sentiment in terms of positive, neutral, and negative sentiment. The compound sentiment evaluates a disclosure sentiment from negative (-1) to positive (+1), based on the calculated sentiment score (see Hutto & Gilbert, 2014).

Perception

Agency and experience Research into mind perception has revealed that agency (the ability of an agent to plan and act) and experience (the ability of the agent to sense and feel) are two key dimensions when valuing an agent's mind (H. M. Gray et al., 2007). To determine whether any differences in mind perception emerged across the testing sessions, participants were requested to evaluate Pepper in terms of agency and experience, after being introduced to these terms (adapted from H. M. Gray et al., 2007). Both concepts were evaluated by the participants using a 0 to 100 rating bar.

Friendliness and warmth This scale was aimed at capturing how participants perceived Pepper in terms of friendliness and warmth using one item from Petty and Mirels (1981) and two items from Birnbaum et al. (2016b), as suggested by Ho et al. (2018). These items were evaluated on a seven-point scale ranging from 1 (not at all) to 7 (extremely). Accordingly, a mean scale was constructed (M = 6.11, SD = 1.02) which was found to be reliable (Cronbach's α = .94).

Communication competency This scale was aimed at capturing how participants experienced and evaluated Pepper's communication competency using an adapted and adjusted version by Croes and Antheunis (2020) for a scale by Demeure, Niewiadomski, and Pelachaud (2011). The scale included three items that were evaluated on a seven-point scale ranging from 1 (not at all) to 7 (extremely). Accordingly, a mean scale was constructed (M = 5.78, SD = 1.18) which was found to be reliable (Cronbach's α = .93).

Interaction quality This scale was aimed at capturing how participants perceived and evaluated the interaction with Pepper using an adapted and adjusted version by Croes and Antheunis (2020) for a scale by Berry and Hansen (2000). Each interaction included two random items out of seven, except for the mid-session (session 5) and the last session (session 10) which included all six items of the scale. These items were evaluated on a seven-point scale ranging from 1 (not at all) to 7 (extremely). Accordingly, a mean scale was constructed (M = 5.48, SD = 1.56) which was found to be reliable (Cronbach's α = .96).

Well being

Mood To capture participants' mood change from their interactions with Pepper, participants reported their mood before and after the interaction with Pepper using the Immediate Mood Scaler (IMS-12; see Nahum et al., 2017). IMS-12 includes 12 items of polarized moods, ranging from 1 (for negative moods) to 7 (for the equivalent positive moods). The scale is a novel validated tool based on the Positive and Negative Affect Schedule (PANAS; Crawford & Henry, 2004), adapted and adjusted to capture current mood states in online and mobile experiments (Nahum et al., 2017). Mean reliable scales were constructed for participants' mood before the interaction (M = 5.35, SD = 1.16, Cronbach's α = .96) and after the interaction (M = 5.75, SD = 1.08, Cronbach's α = .97).

Comforting responses To measure the extent to which participants perceived Pepper's responses as comforting the comforting response scale was adapted (see R. A. Clark et al., 1998). The scale includes 12 self-reported items rated on a seven-point scale, ranging from 1 (I strongly disagree) to 7 (I strongly agree). Accordingly, a mean scale was constructed (M = 5.50, SD = .89) which was found to be reliable (Cronbach's α = .91).

Loneliness Each session participants were requested to report their feelings and thoughts of loneliness from the last three days using the short-form UCLA loneliness scale (ULS-8; see Hays & DiMatteo, 1987). The scale includes 8 items rated on a seven-point scale, ranging from 1 (not at all) to 7 (all the time). Accordingly, a mean scale was constructed (M = 2.86, SD = 1.28) which was found to be reliable (Cronbach's α = .90).

Stress Participants were requested to report their feelings and thoughts of periodic stress from the past month using the perceived stress scale (Cohen et al., 1983). The scale includes 10 statement items rated on a seven-point scale, ranging from 1 (never) to five (very often). A mean scale was constructed (M = 3.30, SD = 1.03) which was found to be reliable (Cronbach's α = .89).

3.3.6 Materials

Zoom video chat

All interactions (video chats) were conducted with the software Zoom, using a university staff account (see figure 4.2). The interactions were recorded using the recording functionality on Zoom and edited to include only those portions of the recordings where participants and/or Pepper were speaking.

Qualtrics questionnaires

All of the questionnaires were administered via the survey software Qualtrics, using a university staff account. In the online questionnaires, the functionality of recording participants' IP addresses was disabled to comply with GDPR guidelines.

3.3.7 Procedure

When recruited, participants completed an induction questionnaire (Session 0) approximately one week before beginning their video chat interactions with Pepper (Sessions 1 to 10). Participants were instructed to have a short conversation with Pepper about several topics that Pepper will bring up, that Pepper will ask them 3 questions and that the interactions will take place twice a week across five weeks during prearranged times. They were further told that each interaction with Pepper should last about 5 to 10 minutes, and another 10-15 minutes will be required to complete questionnaires afterwards. When answering the induction questionnaire (after providing consent to participate in the study), participants were instructed on how to position their video camera for the video chats, and what the lighting in the room is expected to be like. Following this, participants reported on several demographic parameters and several questionnaires (for the full list of questionnaires and their order in each session see the OSF repository; Laban, Kappas, et al., 2020). Participants were redirected to the Prolific website when completing the induction questionnaire (Session 0). A participant number was automatically generated for each participant who completed the induction questionnaire (Session 0) and proceeded to the following sessions. The random assignment of participants to conditions, allocation of topics to sessions for each participant and the order of questions in each interaction were randomized and allocated automatically and an excel sheet was created to help the experimenter control and follow the experimental design procedure for five weeks. See the randomization and allocation code, experimenter notebook with the conditions, allocated topics to a session, and order of questions for each of the participants on the OSF repository (see Laban, Kappas, et al., 2020).

When starting each session, participants were asked to enter their Prolific ID and their participant number. Following, participants were asked to answer the Immediate Mood Scale (IMS-12; Nahum et al., 2017) for reporting their mood before interacting with Pepper. Next, participants received a reminder regarding their interaction with Pepper, what the task requires, and some basic instructions. The page included a link to the Zoom interaction, a frame with the zoom landing page, and the experimenter's e-mail address and instructions on how to communicate with the experimenter in case there are any issues during the interaction. Then,

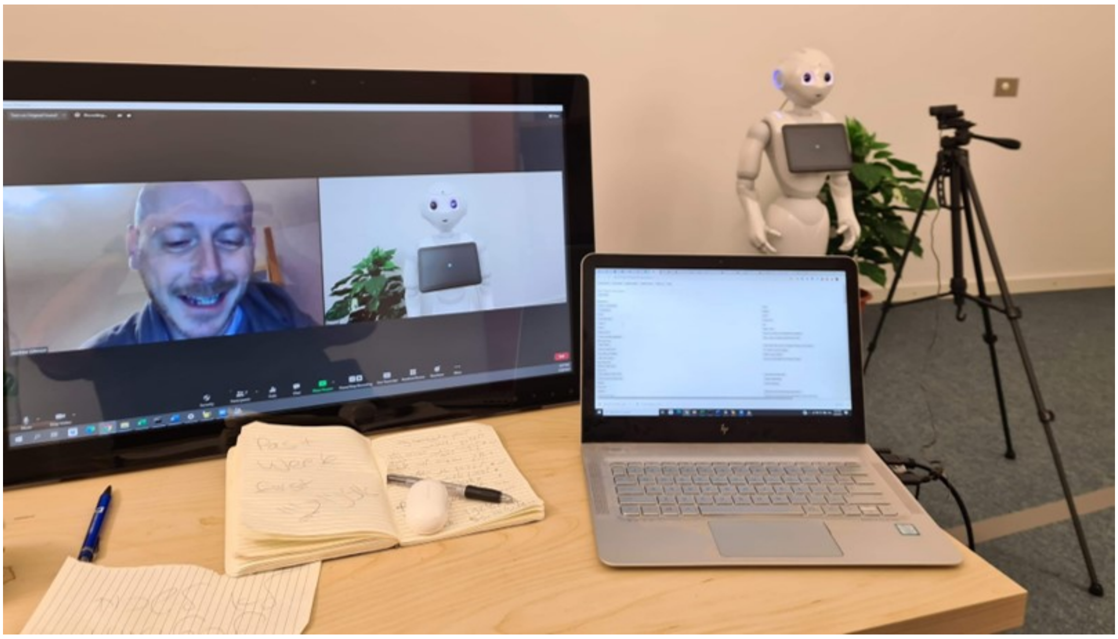

Figure 3.2: The interaction from the eyes of the participants and the experimenter. The participants were exposed only to the robot Pepper (SoftBank Robotics) via the zoom chats.

participants interacted with Pepper via a Zoom video chat (see section 4.3.4), only seeing Pepper in the chat (see figure 4.2). After finishing their interaction with Pepper, participants went back to the Qualtrics page and answered the rest of the questionnaires. The full list of questionnaires and their order in each session can be found on the study's OSF page (see Laban, Kappas, et al., 2020). When finished answering the questionnaire, participants were thanked for the completion of the session, reminded about the date and day of their upcoming session, were provided again with the contact details of the experimenter, and were directed back to Prolific to receive a completion message. When completing the last session participants were clarified that this is indeed the last session, they were thanked for their participation, and provided with contact details of the experimenter to ask any further questions about the study.

3.4 Results

3.4.1 Disclosure

We used lme4 (Bates, Mächler, Bolker, & Walker, 2015) for R to perform a linear mixed effects analysis of the effect of session number, discussion theme and their interaction term on participants' disclosures to Pepper. As fixed effects, we entered the session order, the discussion theme and their interaction term into the model.

Table 3.2: Results of disclosure

	Subjective Disclosure		Duration		Length		Compound Sentiment	
Fixed Effects	*Estimates*	*95%CI*	*Estimates*	*95%CI*	*Estimates*	*95%CI*	*Estimates*	*95%CI*
Intercept	3.33***	2.87 – 3.80	17.62***	7.34 – 27.90	40.78***	16.71 – 64.86	0.41***	0.31 – 0.52
Discussion theme	-0.16	-0.82 – 0.49	4.04	-10.31 – 18.39	9.11	-24.51 – 42.72	-0.04	-0.19 – 0.10
Session number	0.07***	0.03 – 0.11	2.09***	1.45 – 2.74	4.97***	3.47 – 6.47	0.02***	0.01 – 0.04
Discussion theme * Session number	-0.02	-0.07 – 0.04	-0.13	-1.03 – 0.77	-0.09	-2.18 – 2.01	-0.01	-0.02 – 0.01
Random Effects								
SD	0.90		21.04		49.32		0.15	
σ^2	0.56		497.29		2692.53		0.22	
τ_{00}	0.81		442.54		2432.56		0.02	
ICC	0.59		0.47		0.47		0.09	
N	39		39		39		39	
Observations	386		1160		1160		1160	
Marginal R^2 / Conditional R^2	0.034 / 0.605		0.037 / 0.491		0.041 / 0.496		0.021 / 0.108	

*Note: * p<0.05 ** p<0.01 *** p<0.001*

As a random effect, we had intercepts for subjects. Significance was calculated using the lmerTest package (Kuznetsova, Brockhoff, & Christensen, 2017), which applies Satterthwaite's method to estimate degrees of freedom and generate p-values for mixed models.

Subjective self-disclosure

The model explains 60.5% of the variance in participants' *subjective perceptions of their self-disclosure* to Pepper, whereas the fixed effects in the model explain 3.4% of the variance (see table 4.3). The results stress that despite the variance between the participants (SD = .90), the session number has a significant positive fixed effect on participants' subjective perceptions of their self-disclosures (β = .07, SE = .02, p < .001, see figure 4.3). Nevertheless, there were no significant fixed effects in terms of the discussion theme (β = -.16, SE = .33, p = .627), and the interaction term of the session number and discussion theme (β = -.02, SE = .03, p = .529).

Disclosure duration

The model explains 49.1% of the variance in participants' *disclosures duration* (in seconds) to Pepper, whereas the fixed effects in the model explain 3.7% of the variance (see table 4.3). The results stress that despite the variance between the participants (SD = 21.04), the session number has a significant positive fixed effect on participants' disclosures duration (β = 2.10, SE = .33, p < .001, see figure 3.4). Nevertheless, there were no significant fixed effects in terms of the discussion theme (β = 4.04, SE = 7.32, p = .583), and the interaction term of the session number and discussion theme (β = -.13, SE = .46, p = .774).

Another linear mixed effects model was used to test if the discussion theme, the session number, and their interaction term significantly predicted the *disclosure duration* when interacting with the social robot Pepper, including only the items

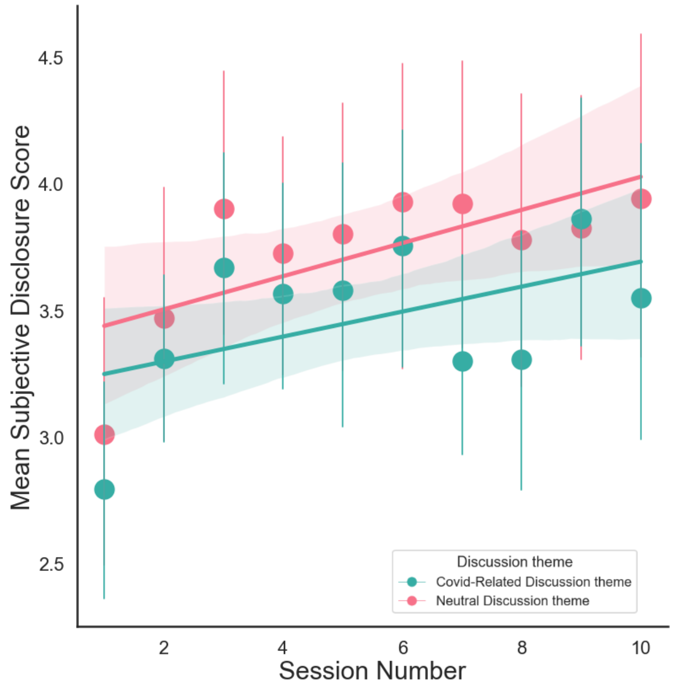

Figure 3.3: Mean subjective disclosure scores by session number and discussion theme.

corresponding to the disclosure topic. The model explains 61.1% of the variance in participants' disclosures duration (in seconds) to Pepper, whereas the fixed effects in the model explain 5.1% of the variance (see table 3.3). The results reveal that despite the variance between participants (SD = 26.53), the session number has a significant positive fixed effect on participants' disclosures duration (β = 2.54, SE = .40, p < .001, see figure 3.4). Nevertheless, no significant fixed effects emerged in terms of the discussion theme (β = 6.50, SE = 9.18, p = .482), and the interaction term of the session number and discussion theme (β = .03, SE = .56, p = .964).

Table 3.3: Results of disclosure including only the items that corresponded to the topic of disclosure.

	Duration		**Length**		**Compound Sentiment**	
Fixed Effects	*Estimates*	*95%CI*	*Estimates*	*95%CI*	*Estimates*	*95%CI*
Intercept	19.29**	6.39 – 32.19	44.20**	14.14 – 74.26	0.48***	0.36 – 0.59
Discussion theme	6.50	-11.51 – 24.51	15.58	-26.40 – 57.56	-0.07	-0.24 – 0.10
Session number	2.54***	1.76 – 3.32	6.09***	4.28 – 7.90	0.02**	0.01 – 0.04
Discussion theme * Session number	0.02	-1.07 – 1.12	0.24	-2.29 – 2.78	-0.01	-0.03 – 0.02
Random Effects						
SD	26.53		61.89		0.13	
σ^2	488.40		2626.54		0.22	
τ_{00}	703.83		3830.41		0.02	
ICC	0.59		0.59		0.07	
N	39		39		39	
Observations	773		773		773	
Marginal R^2 / Conditional R^2	0.051 / 0.611		0.056 / 0.616		0.026 / 0.094	

*Note: * p<0.05 ** p<0.01 *** p<0.001*

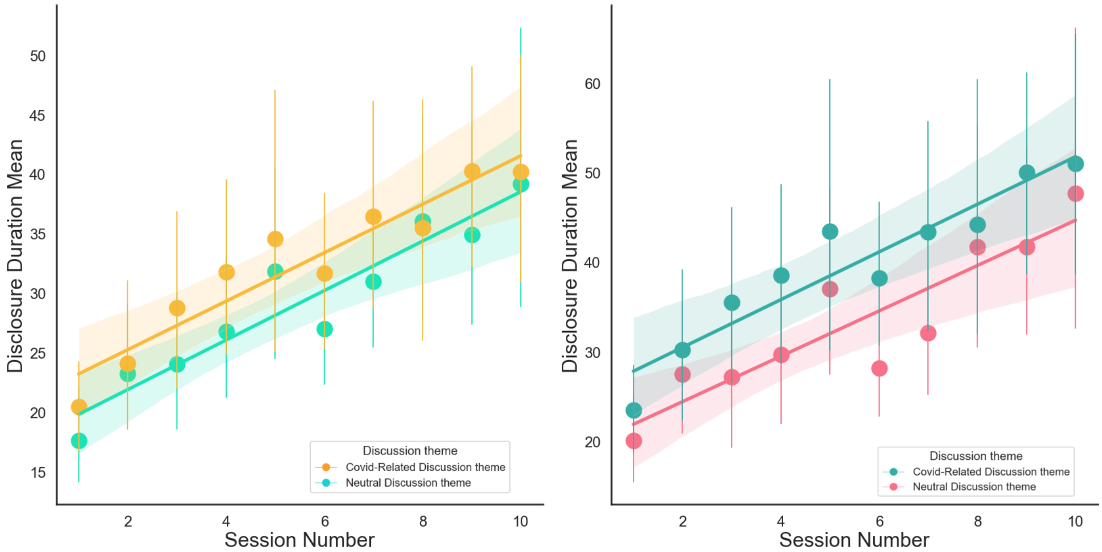

Figure 3.4: From left to right: **(1)** Mean disclosure duration (in seconds) by session number and discussion theme. **(2)** Mean disclosure duration (in seconds) by session number and discussion theme, including only the items corresponding to the disclosure topic.

Disclosure length

The model explains 49.6% of the variance in participants' *disclosures length* (in number of words) to Pepper, whereas the fixed effects in the model explain 4.1% of the variance (see table 4.3). The results stress that despite the variance between the participants (SD = 49.32), the session number has a significant positive fixed effect on participants' disclosures length (β = 4.97, SE = .76, $p <$ .001, see figure 3.5). Nevertheless, no significant fixed effects emerged in terms of the discussion theme (β = 9.11, SE = 17.13, p = .598), and the interaction term of the session number and discussion theme (β = -.09, SE = 1.07, p = .936).

Another linear mixed effects model was used to test if the discussion theme, the session number, and their interaction term significantly predicted the *disclosure length* when interacting with the social robot Pepper, including only the items corresponding to the disclosure topic. The model explains 61.6% of the variance in participants' disclosures length (in number of words) to Pepper, whereas the fixed effects in the model explain 5.6% of the variance (see table 3.3). The results stress that despite the variance between the participants (SD = 61.89), the session number has a significant positive fixed effect on participants' disclosures length (β = 6.09, SE = .92, $p <$ .001, see figure 3.5). Nevertheless, no significant fixed effects emerged in terms of the discussion theme (β = 15.58, SE = 21.39, p = .470), and the interaction term of the session number and discussion theme (β = .24, SE = 1.29, p = .852).

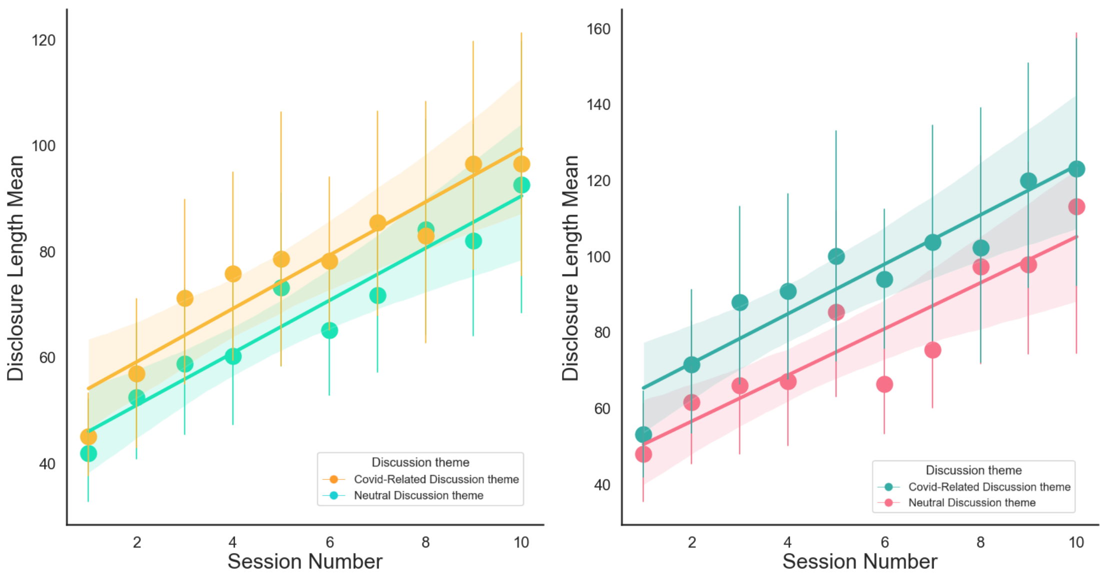

Figure 3.5: From left to right: **(1)** Mean disclosure length (in number of words) by session number and discussion theme. **(2)** Mean disclosure length (in number of words) by session number and discussion theme, including only the items corresponding to the disclosure topic.

Disclosure compound sentiment

The model explains 10.8% of the variance in participants' disclosures *compound sentiment* (see section 3.3.5), whereas the fixed effects in the model explain 2.1% of the variance (see table 4.3). The results stress that despite the variance between the participants (SD = .15), the session number has a significant positive fixed effect on participants' disclosures compound sentiment (β = .02, SE = .01, p < .001). Nevertheless, no significant fixed effects emerged in terms of the discussion theme (β = -.04, SE = .08, p = .569), and the interaction term of the session number and discussion theme (β = -.01, SE = .01, p = .537).

Another linear mixed effects model was run to test if the discussion theme, the session number, and their interaction term significantly predicted the disclosure *compound sentiment* when interacting with the social robot Pepper, including only the items that corresponded to the topic of disclosure. The model explains 9.4% of the variance in participants' disclosures compound sentiment to Pepper, whereas the fixed effects in the model explain 2.6% of the variance (see table 3.3). The results stress that despite the variance between the participants (SD = .13), the session number has a significant positive fixed effect on participants' disclosures duration (β = .02, SE = .01, p = .005). Nevertheless, no significant fixed effects emerged in terms of the discussion theme (β = -.07, SE = .09, p = .418), and the interaction term of the session number and discussion theme (β = -.01, SE = .01, p = .575).

Table 3.4: Results of linear mixed effects analysis of session number, discussion theme, and the interaction term on participants' social perceptions of Pepper.

	Agency		**Experience**		**Friendliness and Warmth**	
Fixed Effects	*Estimates*	*95%CI*	*Estimates*	*95%CI*	*Estimates*	*95%CI*
Intercept	62.61***	52.48 – 72.74	55.66***	44.01 – 67.30	5.83***	5.38 – 6.27
Discussion theme	-1.34	-15.49 – 12.81	-3.59	-19.386 – 12.67	-0.07	-0.69 – 0.55
Session number	1***	0.50 – 1.49	1.82***	1.18 – 2.45	0.05***	0.02 – 0.07
Discussion theme * Session number	0.08	-0.62 – 0.77	-0.11	-1.00 – 0.78	0.02	-0.01 – 0.05
Random Effects						
SD	21.38		24.29		0.93	
σ^2	98.61		160.95		0.23	
τ_{00}	457.23		589.89		0.86	
ICC	0.82		0.79		0.79	
N	39		39		39	
Observations	386		386		386	
Marginal R^2 / Conditional R^2	0.016 / 0.825		0.038 / 0.794		0.025 / 0.797	

*Note: * p <0.05 ** p <0.01 *** p <0.001*

3.4.2 Perception

We used lme4 (Bates et al., 2015) for R to perform linear mixed effects analysis of the effect of session number, discussion theme and their interaction term on participants' perceptions of Pepper, including perceptions of agency and experience (see H. M. Gray et al., 2007), friendliness and warmth, communication competency and interaction quality. As fixed effects, we entered the session order, the discussion theme and their interaction term into the model. As a random effect, we had intercepts for subjects. Significance was calculated using the lmerTest package (Kuznetsova et al., 2017), which applies Satterthwaite's method to estimate degrees of freedom and generate p-values for mixed models.

Agency

The model explains 82.5% of the variance in participants' perceptions of Pepper's degree of *agency*, whereas the fixed effects in the model explain 1.6% of the variance (see table 3.4). The results stress that despite the variance between the participants (SD = 21.38), the session number has a significant positive fixed effect on participants' perceptions of Pepper's degree of agency ($\beta = 1$, $SE = .25$, $p < .001$, see figure 3.6). Nevertheless, no significant fixed effects emerged in terms of the discussion theme (β = -1.34, SE = 7.20, p = .853), and the interaction term of the session number and discussion theme (β = .08, SE = .35, p = .828).

Experience

The model explains 79.4% of the variance in participants' perceptions of Pepper's degree of *experience*, whereas the fixed effects in the model explain 3.8% of the variance (see table 3.4). The results stress that despite the variance between the

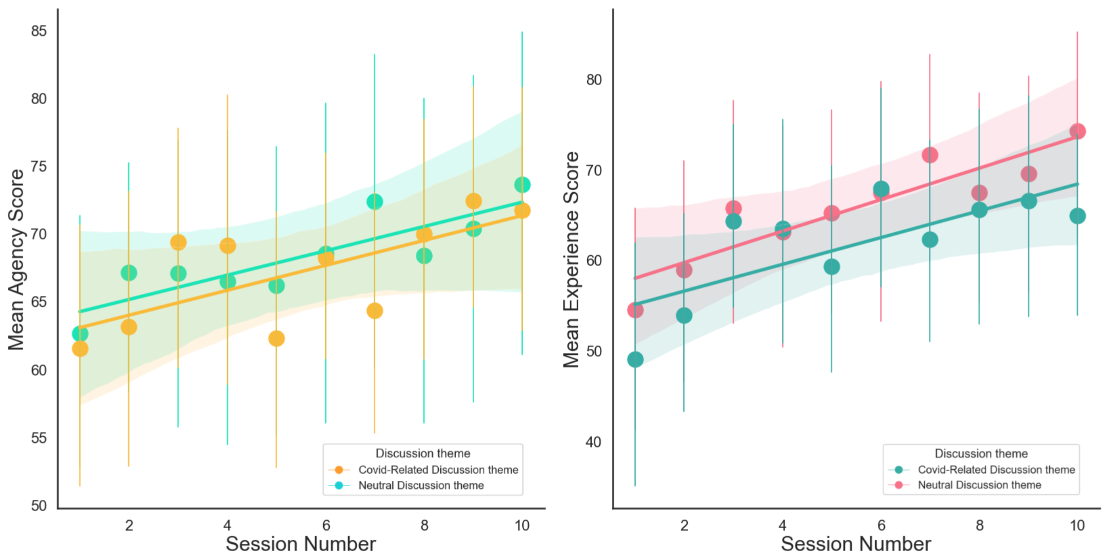

Figure 3.6: From left to right: **(1)** Mean agency scores by session number and discussion theme. **(2)** Mean experience scores by session number and discussion theme.

participants ($SD = 24.29$), the session number has a significant positive fixed effect on participants' perceptions of Pepper's degree of experience ($\beta = 1.82$, $SE = .32$, $p < .001$, see figure 3.6). Nevertheless, no significant fixed effects emerged in terms of the discussion theme ($\beta =$ -3.59, $SE = 8.27$, $p = .666$), and the interaction term of the session number and discussion theme ($\beta =$ -.11, $SE = .45$, $p = .811$).

Friendliness and warmth

The model explains 79.7% of the variance in participants' perceptions of Pepper's degree of *friendliness and warmth*, whereas the fixed effects in the model explain 2.5% of the variance (see table 3.4). The results stress that despite the variance between the participants ($SD = .93$), the session number has a significant positive fixed effect on participants' perceptions of Pepper's degree of friendliness and warmth ($\beta = .05$, $SE = .01$, $p < .001$). Nevertheless, no significant fixed effects emerged in terms of the discussion theme ($\beta =$ -.07, $SE = .32$, $p = .828$), and the interaction term of the session number and discussion theme ($\beta = .02$, $SE = .02$, $p = .245$).

Communication competence

The model explains 70.3% of the variance in participants' perceptions of Pepper's *communication competence*, whereas the fixed effects in the model explain 1.2% of the variance (see table 3.5). The results stress that despite the variance between the participants ($SD = 1$), the session number has a significant positive fixed effect on participants' perceptions of Pepper's communication competence ($\beta = .03$, SE

Table 3.5: Results of linear mixed effects analysis of session number, discussion theme, and the interaction term on participants' usability-related perceptions of Pepper.

	Communication Competency		**Interaction Quality**	
Fixed Effects	*Estimates*	*95%CI*	*Estimates*	*95%CI*
Intercept	5.61***	5.12 – 6.11	4.97***	4.33 – 5.60
Discussion theme	-0.07	-0.85 – 0.53	-0.21	-1.10 – 0.68
Session number	0.03*	0.00 – 0.07	0.09***	0.05 – 0.14
Discussion theme * Session number	0.02	-0.03 – 0.06	0.03	-0.03 – 0.10
Random Effects				
SD	1		1.26	
σ^2	0.43		0.85	
τ_{00}	1		1.59	
ICC	0.70		0.65	
N	39		39	
Observations	386		386	
Marginal R^2 / Conditional R^2	0.012 / 0.703		0.041 / 0.664	
*Note: * p <0.05 ** p <0.01 *** p <0.001*				

= .02, p = .040). Nevertheless, no significant fixed effects emerged in terms of the discussion theme (β = -.16, SE = .35, p = .655), and the interaction term of the session number and discussion theme (β = .02, SE = .02, p = .456).

Interaction quality

The model explains 66.4% of the variance in participants' perceptions of the *interaction quality*, whereas the fixed effects in the model explain 4.1% of the variance (see table 3.5). The results stress that despite the variance between the participants (SD = 1.26), the session number has a significant positive fixed effect on participants' perceptions of the interaction quality (β = .09, SE = .02, $p < .001$). Nevertheless, no significant fixed effects emerged in terms of the discussion theme (β = -.21, SE = .45, p = .646), and the interaction term of the session number and discussion theme (β = .04, SE = .03, p = .291).

3.4.3 Well-being

We used lme4 (Bates et al., 2015) for R to perform linear mixed effects analysis of the effects of session number, discussion theme and their interaction term on participants' perceptions of Pepper's comforting responses, mood change, and feelings of loneliness. As fixed effects, we entered the session order, the discussion theme and their interaction term into the model. As a random effect, we had intercepts for subjects. Significance was calculated using the lmerTest package (Kuznetsova

Table 3.6: Results of linear mixed effects analysis of session number, discussion theme, their interaction term, mood change, and the interaction term of mood change and session number on participants' moods and perceptions of Pepper's comforting responses.

	Mood		**Comforting Responses**	
Fixed Effects	*Estimates*	*95%CI*	*Estimates*	*95%CI*
Intercept	5.23***	4.77 – 5.69	5.10***	4.72 – 5.47
Discussion theme	-0.24	-0.87 – 0.40	.13	-.40 – .66
Session number	0.03*	0.01 – 0.06	0.07***	0.04 – 0.09
Mood change	0.48***	0.27 – 0.70		
Discussion theme * Session number	0.02	-0.01 – 0.05	-0.01	-0.04 – 0.02
Discussion theme * Mood change	-0.01	-0.19 – 0.17		
Session number * Mood change	-0.01	-0.05 – 0.02		
Random Effects				
SD	0.94		0.79	
σ^2	0.41		0.18	
τ_{00}	0.89		0.62	
ICC	0.68		0.77	
N	39		39	
Observations	772		386	
Marginal R^2 / Conditional R^2	0.042 / 0.698		0.039 / 0.783	

*Note: * p <0.05 ** p <0.01 *** p <0.001*

et al., 2017), which applies Satterthwaite's method to estimate degrees of freedom and generate p-values for mixed models.

Mood

The model explains 69.8% of the variance in participants' *mood*, whereas the fixed effects in the model explain 4.2% of the variance (see table 3.6). The results stress that despite the variance between the participants (SD = .94), we observed a positive significant fixed effect on mood change, as participants reported a positive mood change after interacting with Pepper (β = .49, SE = .11, p < .001). Moreover, the session number has a significant positive fixed effect on participants' mood (β = .03, SE = .33, p = .019, see figure 3.7). Nevertheless, no significant fixed effects emerged in terms of the discussion theme (β = -.24, SE = .32, p = .469), the interaction term of the session number and discussion theme (β = .02, SE = .02, p = .154), the interaction term of the session number and mood change (β = -.01, SE = .02, p = .388), and the interaction term of the discussion theme and mood change (β = -.01, SE = .09, p = .943).

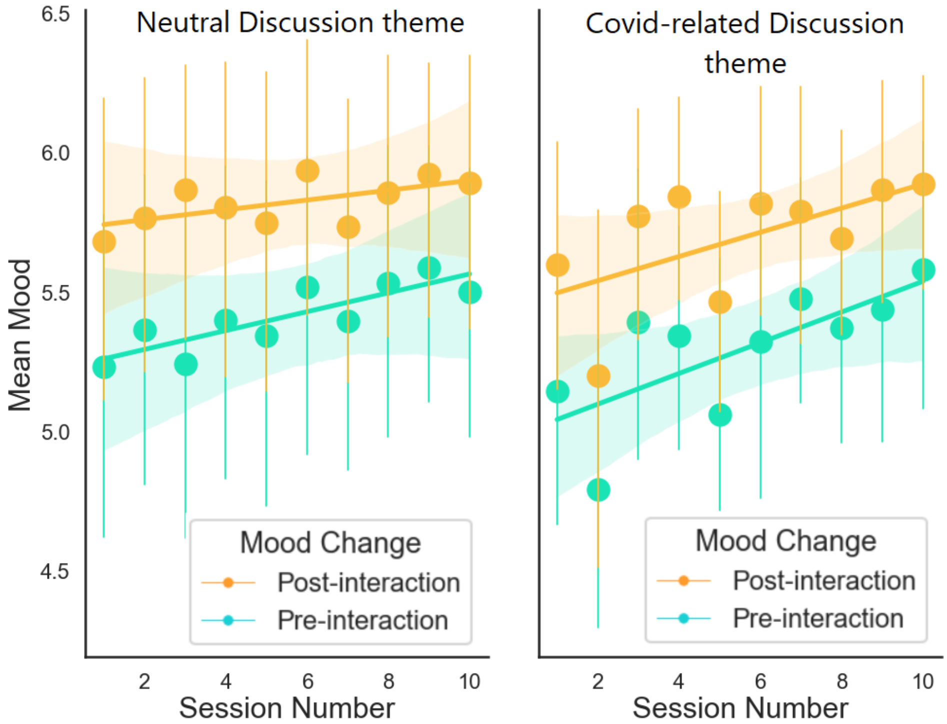

Figure 3.7: From left to right: **(1)** Mean mood scores of participants in the neutral discussion theme, before and after the interaction, by session number. **(2)** Mean mood scores of participants in the Covid-related discussion theme, before and after the interaction, by session number.

Comforting responses

The model explains 78.3% of the variance in participants' perceptions of Pepper's *comforting responses*, whereas the fixed effects in the model explain 3.9% of the variance (see table 3.6). The results stress that despite the variance between the participants (SD = .79), the session number has a significant positive fixed effect on participants' perceptions of Pepper's comforting responses (β = .07, SE = .01, $p <$ .001, see figure 3.8). Nevertheless, no significant fixed effects emerged in terms of the discussion theme (β = .13, SE = .27, p = .635), and the interaction term of the session number and discussion theme (β = -.01, SE = .02, p = .540).

Loneliness

The model explains 75.9% of the variance in participants' feelings of *loneliness*, whereas the fixed effects in the model explain 7.8% of the variance (see table 3.7). The results stress that despite the variance between the participants (SD = 1.08), the session number has a significant negative fixed effect on participants' feelings of loneliness (β = -.05, SE = .01, $p <$ .001, see figure 3.8). Nevertheless, no significant fixed effects emerged in terms of the discussion theme (β = .63, SE

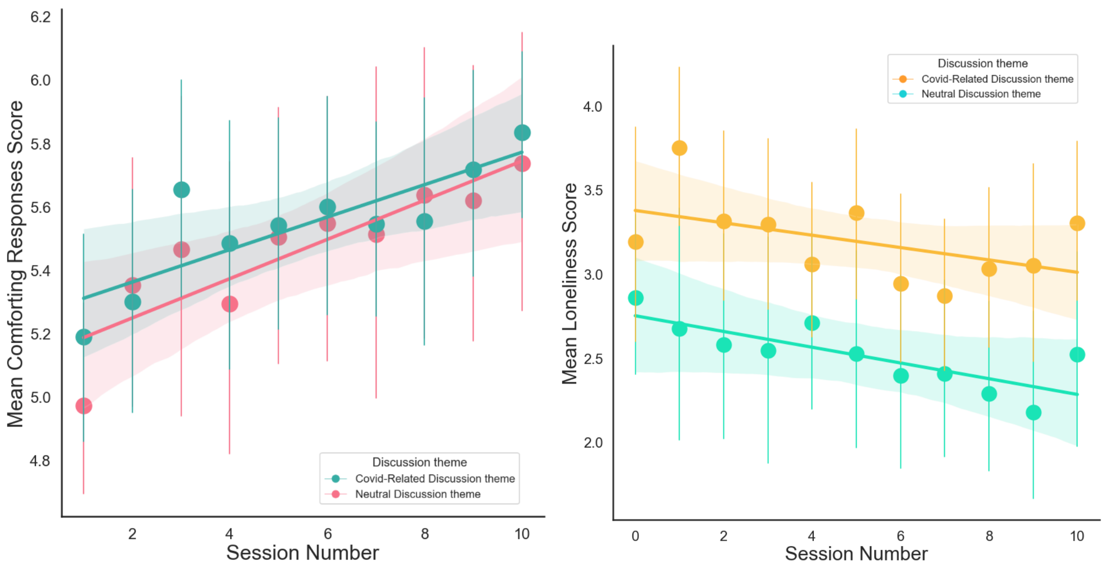

Figure 3.8: From left to right: **(1)** Mean comforting responses scores by session number and discussion theme. **(2)** Mean loneliness scores by session number and discussion theme.

= .37, p = .091), and the interaction term of the session number and discussion theme (β = .01, SE = .02, p = .674).

Another linear mixed effects model was used, omitting the data units collected in the induction session (session 0) before the exposure to the discussion theme manipulation, in order to have a better evaluation of the effect of the discussion theme on participants' feelings of *loneliness*. The model explains 79.1% of the variance in participants' feelings of loneliness, whereas the fixed effects in the model explain 8.4% of the variance (see table 3.7). The results stress that despite the variance between the participants (SD = 1.10), the session number has a significant negative fixed effect on participants' feelings of loneliness (β = -.04, SE = .02, p = .008), and the discussion theme has a significant fixed effect on participants' feelings of loneliness (β = .77, SE = .38, p = .046, see figure 3.8). Participants in the COVID-related experiences discussion theme group reported higher levels of loneliness compared to participants in the general experiences discussion theme group. Nevertheless, no significant fixed effect emerged in terms of the interaction term of the session number and discussion theme (β = -.01, SE = .02, p = .575) on participants' feelings of loneliness.

Stress

The model explains 77.3% of the variance in participants' feelings of *stress*, whereas the fixed effects in the model explain 9.4% of the variance (see table 3.7). The results stress that despite the variance between the participants (SD = .86), the discussion theme has a significant fixed effect on participants' feelings of stress

Table 3.7: Results of linear mixed effects analysis of session number, discussion theme, their interaction term on participants' feelings of loneliness and stress.

	Loneliness		Loneliness (without session 0)		Stress	
Fixed Effects	*Estimates*	*95%CI*	*Estimates*	*95%CI*	*Estimates*	*95%CI*
Intercept	2.76***	2.24 – 3.27	2.71***	2.18 – 3.24	2.70***	2.05 – 3.34
Discussion theme	.63	-0.09 – 1.35	0.77*	0.03 – 1.51	1.31**	0.41 – 2.22
Session number	-0.05***	-0.08 – -0.02	-0.04**	-0.07 – -0.01	0.04	-0.02 – 0.11
Discussion theme * Session number	0.01	-0.03 – 0.05	-0.01	-0.05 – 0.03	-0.10*	-0.19 – -0.01
Random Effects						
SD	1.08		1.10		0.86	
σ^2	0.41		0.36		0.25	
τ_{00}	1.16		1.21		0.74	
ICC	0.74		0.77		0.75	
N	39		39		39	
Observations	425		386		78	
Marginal R^2 / Conditional R^2	0.078 / 0.759		0.084 / 0.791		0.094 / 0.773	

*Note: * p <0.05 ** p <0.01 *** p <0.001*
For stress, 'Session number' is a dummy variable of sessions 5 and 10 (5 = 0).

(β = 1.31, SE = .45, p = .005). Participants in the COVID-related experiences discussion theme group reported higher levels of stress compared to participants in the general experiences discussion theme group. Moreover, the interaction term of the session number and discussion theme also has a significant fixed effect on participants' feelings of stress (β = -.01, SE = .05, p = .042) with participants in the COVID-related experiences discussion theme group reporting that their feelings of stress decreased from the fifth session to the tenth, whereas participants in the general experiences discussion theme group reported for increasing levels of stress from the fifth session to the tenth. Finally, no significant fixed effect emerged in terms of the session number across the entire sample (β = .04, SE = .03, p = .205).

3.5 Discussion

Here we have introduced a novel long-term mediated experimental design aimed at testing the extent to which a social robot elicits and affects peoples' disclosures to the robot, and how perceptions of the robot develop over time. Moreover, we measured the extent to which the interactions with the social robot affected participants' well-being in different ways across time. Participants conversed with the social robot Pepper 10 times over 5 weeks about one of two different topics depending on random group assignment. One group's conversation topics were framed within the context of the Covid-19 pandemic (e.g., social relationships during the pandemic, sustaining mental health during the pandemic, etc.), whereas the other group's conversation topics were similar, except no explicit mention of the Covid-19 pandemic was ever made. We evaluated the effect of time (session number) as well as how the discussion theme affected participants, comparing general everyday topics, to the same topics framed to the COVID-19 pandemic to address a more emotional context.

3.5.1 People self-disclose increasingly more to a social robot over time

Our first key finding shows that across the 10 sessions studied here, people speak for a longer time and share more information in their disclosures to the social robot Pepper. Moreover, consistent with previous results (Laban, George, et al., 2021), subjective perceptions of self-disclosure align well with the objective data, and correspond to observed evidence of the length and duration of the disclosure, as people correctly perceived themselves to gradually share more information with Pepper across sessions. Finally, we found that people were more positive in their disclosures over time. The effects described here were even more meaningful when addressing only disclosures that are related to the session's conversation topic. Nevertheless, our results also stressed that the discussion theme has no meaningful nor significant effect on participants' disclosures to Pepper. Self-disclosure is a dynamic and socially complex human behaviour (Jourard & Lasakow, 1958; Pearce & Sharp, 1973), and accordingly, this key finding contributes to our understanding of humans' social behaviour and communication with robots. While numerous prior studies have exported humans' social behaviour towards robots in single-session studies, our knowledge of how people's behaviours towards robots change or develop over the longer-term remain limited in social HRI. Naturally, we recognize that people are different and might adapt different behavioural patterns when conversing with social robots. Nonetheless, we showed that people self-disclosed increasingly more to Pepper over time in a systematic fashion even when the potential for such interindvidiual differences are taken int account through the use of rigorous methodology. This is a meaningful contribution to HRI theory, showing that prolonged and intensive interactions with social robots can overcome novelty effects from behavioural objective evidence and not only from users' self-reported subjective perceptions.

3.5.2 People perceive a robot as more social and competent over time

We found that across the 10 sessions, participants attributed higher qualities of mind (see H. M. Gray et al., 2007), in terms of agency and experience. Likewise, over time participants found Pepper to be friendlier and warm, as well as Pepper's communication skills more competent. Finally, across time, participants also rated the interactions with Pepper to be of increasingly higher quality. Here again, our results stress that the discussion theme has no meaningful nor significant effect on the way people perceive Pepper and the interaction. This key finding highlights the extent of people's social perception of robots over time. Despite Pepper's limited responses, over time participants attributed more social qualities to this particular robot, thus providing evidence for the influence of social engagement with a robot on its social perception over time. Furthermore, beyond finding Pepper to be more social, participants also attributed higher degrees of competency to Pepper over time. It is of note that people's perceptions of the robot and the interactions corresponded to their self-disclosure behaviour toward the robot over time. This key finding supports previous research showing how people's behaviours aligned with their social perceptions and attitudes towards the robot in single-session interactions (Stower et al., 2022). Here we provided further support for this behavioural mechanism in HRI, and our results demonstrate how perceptions of robots and behaviours toward robots co-align over time during prolonged interactions.

3.5.3 Establishing relationships with social robots

While previous longitudinal studies often report novelty effects in human–machine communication encounters (e.g., Croes & Antheunis, 2020, 2021), here we see a clear opposing trend, with evidence rooted in people's objective behaviour to robots (i.e., with the length and quality of participant disclosures increasing over time) and their subjective perceptions of robots (i.e., with participants' social perceptions of Pepper increasing over time, in terms of Pepper's agency, experience, friendliness and warmth, communication competency, and the interaction quality). These findings are particularly interesting as they provide clear evidence for social robots' potential to establish meaningful relationships with human users. While consistent with previous suggestions on the matter (see Fox & Gambino, 2021; Nielsen, Pfattheicher, & Keijsers, 2022), the present study provides initial support for long-term relationships between humans users and a social robot, supported with multidimensional data. Furthermore, our findings establish important foundations for future HRI studies looking into how human-robot relationships develop over time, as well as for roboticists trying to create meaningful relationships between their robots and their users. Finally, these results highlight how human–robot relationships could act as ideal settings for robotic interventions for well-being. In addition, compared to Croes's previous studies (e.g., Croes & Antheunis, 2020, 2021) and despite our previous results in single-session studies (see Laban, George, et al., 2021), the present study suggests differences between embodied and disembodied agents in long-term interactions. We assume that people might attribute more social qualities to embodied agents (for the scope of this study, social robots) and accordingly, the relationship with such agents should evolve over time and not experience the same degree of novelty effects as experienced in Croes and Antheunis (2020, 2021). Nevertheless, this calls for further investigation and clear opportunities exist for future research to address the effects of embodiment on relationship establishment with artificial agents.

Our results further support the notion that the social dynamic in HRI, where humans often seek to establish social connections and rapport with robots, influences people's perceptions and attitudes towards the robot. The results of the present study further confirmed that mere-exposure effect (Zajonc, 2001) in HRI operates differently compared to traditional HCI, as the focus shifts from usability to the establishment of social bonds. By simulating human-like behaviours and engaging in social interactions, social robots, like the Pepper robot used in the present study, can elicit positive responses and be perceived as increasingly socially competent over time. This highlights the importance of understanding the dynamics of human–robot communication in long-term interactions and the potential for social robots to establish meaningful relationships with human users (Cross & Ramsey, 2021). This distinction becomes evident when examining prolonged social interactions with a robot, resulting from repeated exposure. In the current context, we observe that these interactions demonstrate increasingly social behaviour and perception, representing the richest form of adaptation toward a social robot. Our findings suggest that users are not solely treating the Pepper robot used here as an object, but are willing to engage in long-term social interactions, and perhaps even establish some form of social connection with Pepper. Thus, our study highlights the difference between learning how to use an object through repeated usage, as observed in traditional HCI studies (see Van Giesen et al., 2015), and the social behaviour and perception exhibited toward a robot in HRI settings. This distinction emphasizes the unique nature of social interaction in HRI and the need for a deeper understanding of human–robot communication beyond traditional usability perspectives.

3.5.4 Talking to robots positively affects people's well-being

In terms of well-being, we found that participants' moods improved after interacting with Pepper, and also across the 10 sessions. Moreover, across the 10 sessions, participants reported Pepper's responses to be more comforting. Our results revealed that the discussion theme per se did not have a meaningful or significant effect on people's moods and on the way people perceived Pepper's comforting responses. These findings provide further valuable evidence for the positive outcomes of employing a social robot as an intervention supporting people's well-being. Moreover, our results here add to previous studies (e.g., Bodala et al., 2021; M. Axelsson et al., 2022; Jeong et al., 2022) that show the benefits of using robots for emotional support. Taken together with other results from this study (i.e., that people self-disclose increasingly more to a social robot over time and that people perceive a robot as more social over time), this study provides crucial evidence for establishing relationships with robots in health and care settings. These findings contribute to the introduction of social robots as conversational partners, and how this type of verbal interaction could support people with emotional regulation by talking about stressors and well-being. Simple tasks, like the one described in the study, are relatively easy to administer automatically in HRIs (by focusing on providing general and broad responses to users' disclosures) but can simulate effective procedures via self-disclosure like affect labelling (Torre & Lieberman, 2018) and other emotional introspective processes with users self-reflecting on their emotions and behaviours (Tamir & Mitchell, 2012). Accordingly, social robots can offer meaningful opportunities for self-managed interventions designed to support people's emotional health and well-being.

Another key finding in this regard has to do with people's feelings of loneliness. We found that over time across the experiment, participants reported feeling significantly less lonely. Loneliness is both a risk factor and a symptom of mental disorders and is a significant and growing public health issue with many comorbidities (Hawkley & Cacioppo, 2010). The recent COVID-19 pandemic stressed loneliness's tremendous effect on individuals' lives and society and highlighted the need for accessible intervention and support (Lampraki, Hoffman, Roquet, & Jopp, 2022). Social robots are often discussed as potential companions for people suffering from loneliness (see Pirhonen, Tiilikainen, Pekkarinen, Lemivaara, & Melkas, 2020; Ruggiero et al., 2022; Odekerken-Schröder et al., 2020), especially concerning the Covid-19 pandemic (e.g., Scassellati & Vázquez, 2020) with growing media attention (e.g., Engelhart, 2021) and public initiatives (see Chang, 2022). Our results here further support that using objective and systematic measures, showing that repeated interactions with social robots reduced people's feelings of loneliness. This calls for further innovation and future research targeting loneliness as a public health issue using social robots.

3.5.5 Robots that discuss emotional content can simulate feelings

Consistent with previous results in single-session HRIs (Laban, George, et al., 2021), the discussion theme did not affect people's self-disclosure toward social robots or the way they perceived the robot or the interaction. However, our results do suggest that framing a discussion with a robot around a more emotional topic may elicit more emotional feelings among participants. This was specifically observed in this study with feelings of loneliness and stress. Our results here showed that when Pepper addressed the COVID-19 pandemic, participants reported higher levels of loneliness and stress, compared to participants in the general experiences discussion theme group. This important finding provides initial support for the notion that robots can trigger an emotional reaction from the interaction's content. When studying robots' affective capabilities, previous studies often address factors related to the robot's visual features (e.g., embodiment) or robotic functionalities (e.g., emotional recognition; Spitale & Gunes, 2022). Yet, studies aiming at developing and assessing social robotic interventions for well-being should also study the robot's ability to simulate human affect in different ways (see Spitale & Gunes, 2022). Our results highlight the role of content and frame when aiming to simulate human emotions and feelings during HRIs. they further show that robots can trigger complex emotions when addressing meaningful and personal moments and events. Nonetheless, our evidence here is based solely on two factors of loneliness and stress, answering to one emotional frame - mentioning the Covid-19 pandemic. Thus, for further understanding humans' emotional response to social robotic stimuli, this should be studied with various feelings and emotions, within several settings and in response to different frames.

It is important to acknowledge that the limited differences observed between the conditions in this study may be attributed to ceiling effects. This could be because the study took place during the peak of the pandemic, causing participants to primarily focus on the consequences of the pandemic regardless of their assigned condition. Therefore, future studies should explore the most effective approach to manipulate emotional themes during experimental social interactions with social robots. While there are established emotion-elicitation techniques used in human-human social interaction research (Bujarski, Mischel, Dutton, Steele, & Cisler, 2015), it may be challenging to seamlessly integrate them into HRI behavioural paradigms. It is recommended that researchers further examine these techniques and evaluate their capacity to evoke varying levels of emotion in social interactions with robots.

3.5.6 Methodological contribution

Through the present research, we aimed to establish experimental methods that researchers from HRI, as well as from a number of related fields, including psychology, psychiatry, social work, anthropology, and computer science, might wish to use to further explore people's perceptions of a sociable, humanoid robot in natural everyday settings during prolonged conversational interactions. Beyond exploring general questions regarding how people engage with a social robot from their home settings and how it supports their well-being, the current research also provides a means to further examine the impact of novelty effects, and the impact of long-term social engagement with a robot on behaviour (c.f., Cross, Riddoch, et al., 2019). Furthermore, this study can be replicated and tested with various populations, clinical and healthy, in order to understand how social robots could be introduced in different care settings and as interventions using speech-based interactions (c.f., Laban, Morrison, Kappas, & Cross, 2022). By introducing this novel paradigm in detail here, and documenting results from a rigorous empirical study using this paradigm, we aim to provide a tool that we hope will be of use to the HRI research community more broadly, while also assisting with facilitating research rigour and reproducibility (Gunes et al., 2022; Henschel et al., 2020, 2021; Cross & Ramsey, 2021), as well as the development of data-centric robotic models (c.f., Powell et al., 2022; Abbasi et al., 2022). Moreover, we would argue that the online computer-mediated means of human-robot communication used in this experimental design can overcome some of the challenges and barriers that are related to long-term HRI studies in natural ecologically valid settings (such as the costs associated with sending individual robots home for an extended period of time with participants) and suggest alternative means for conducting HRI research in people's natural settings.

3.6 Conclusion

These results set the stage for addressing social robots as conversational partners in social settings, and how this type of verbal interaction could support people with emotional regulation by talking about stressors and well-being. The study provides crucial evidence for establishing relationships with robots, and their potential introduction as interventions supporting people's emotional health through encouraging self-disclosure. These results provide meaningful evidence for user experience, acceptance, and trust of social robots and other conversational agents (Law, Følstad, Grudin, & Schuller, 2022; Porcheron et al., 2022), highlighting how the perception of robots and behaviour towards them is closely related. These results hold several implications for assessing interactions as well as interventions with socially assistive robots, and for HRI research in general. Future research is encouraged to replicate and reproduce the current findings with different robots and different populations. In doing so, this will help to overcome the vast challenges and barriers that are related to long-term HRI studied in natural ecologically valid settings.

Chapter 4

Coping with Emotional Distress via Self-Disclosure to Robots: Intervention with Caregivers

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A preliminary version of this chapter was accepted for publication and presentation at *ACM Conference on Human Factors in Computing Systems (CHI) 2022* under the title: "Informal caregivers disclose increasingly more to a social robot over time" (see Laban, Morrison, et al., 2022), and a full version of this chapter was submitted for publication in *Computers in Human Behavior* on 07/02/2023 (see Laban, Morrison, et al., 2023).

Abstract

People often engage in various forms of self-disclosure and social sharing with others when trying to regulate the impact of emotional distress. Here we introduce a novel long-term mediated intervention aimed at supporting informal caregivers to cope with emotional distress via self-disclosing their emotions and needs to a social robot. Research has shown that informal caregivers often struggle in managing the emotional and practical demands of the caregiving situation, and also highlights the lack of social support and paucity of social interaction some experience. Accordingly, we were interested in the extent of informal caregivers' self-disclosure behaviour towards a social robot (Pepper, SoftBank Robotics) over time, and how (social and usability-related) perceptions of the robot develop over time. Moreover, we wished to examine how this intervention made informal caregivers feel (in terms of reported mood, perceptions of the robot as comforting, feelings of loneliness, and stress), and the extent to which interacting with the robot affected these individuals' emotion regulation. Informal caregivers conversed with the social robot Pepper 10 times across 5 weeks about general everyday topics. Our results show that informal caregivers self-disclosed increasingly more to the robot across time and perceived it as increasingly social and competent over time. Furthermore, participants' moods positively changed after interacting with the robot, which they perceived more comforting over time. Participants also reported feeling increasingly less lonely and stressed. Finally, our results showed that after self-disclosing to the robot for 5 weeks, informal caregivers reported being more accepting of their caregiving situation, reappraising it more positively, and experiencing fewer feelings of blame towards others. These results set the stage for situating social robots as conversational partners in social settings, as well as highlight how communicating with social robots holds potential for providing emotional support for people coping with emotional distress.

4.1 Introduction

Emotional distress can be defined as an unpleasant emotional state that occurs when one has limited abilities or is unable to adapt to stressors and to their consequences, both perceived and actual (Ridner, 2004). As a wealth of literature attests, emotional distress is one of the most common human emotional experiences. It can arise from various situations and stressors ranging from unexpected calamities (e.g., grief and loss, natural or man-made disasters, or physical or mental illness) to typical annoying daily events (Anisman & Merali, 1999). The feeling of persistent emotional distress widely and negatively impacts people's well-being, and carries other mental and physical health implications (Barry et al., 2020) ranging from psychiatric disorders and psychopathologies (e.g., depression and anxiety) (G. W. Brown, 1993) to immune system dysfunction (Herbert & Cohen, 1993). One meaningful way of coping with emotional distress and its associated comorbidities is by exercising emotion regulation, a set of internal and external processes and techniques that involve monitoring, assessing, and modifying one's state behaviour or cognition in a given situation (Gross, 1998). While some self-regulation techniques (e.g., reappraisal, affect labeling, etc.) are highly supportive, when going through difficult times people are often prone to adapting maladaptive emotion regulation strategies (e.g., suppression) (Sheppes, Scheibe, Suri, & Gross, 2011) that can cause long-lasting harm to one's well-being (John & Gross, 2004). For many, exercising constructive emotion regulation is not an easy task (Gross, 2002) and engaging in various forms of interpersonal communication behaviours like self-disclosure and social sharing with others effectively support this process (Coan, 2012; Rimé, 2009; Zaki & Williams, 2013). Self-disclosure is a communication behaviour aimed at introducing and revealing oneself to others, and it plays a key role in building relationships between individuals (Jourard & Lasakow, 1958; Pearce & Sharp, 1973). Numerous health advantages have been associated with engaging in different types of self-disclosure, including the ability to elicit and provide support and improve mood, and offer a comfortable setting for sharing feelings (Coan, 2012; Rimé, Mesquita, Philippot, & Boca, 1991; Rimé, 2009; Zaki & Williams, 2013; Rimé, Bouchat, Paquot, & Giglio, 2020).

One group of people that has been shown to be particularly prone to emotional distress is informal caregivers (Pearlin et al., 1990; Hiel et al., 2015; Collins & Kishita, 2020b; Gérain & Zech, 2019). Informal caregivers provide care and support to a friend or family member while typically being unpaid and non-formally trained. Their care recipients often suffer from chronic health conditions that are related to old age or a variety of physical and mental health conditions (Revenson et al., 2016c). While many informal caregivers find the caregiving experience to be rewarding (Zarzycki & Morrison, 2021; Zarzycki, Morrison, Bei, & Seddon, 2022), this experience is also often associated with serious health and well-being implications for the informal caregivers themselves (Revenson et al., 2016c, 2016b, 2016a). The caregiving situation is considered to be a potential stressor (Pearlin et al., 1990), which might lead to a variety of negative health and well-being outcomes including physical and emotional strain, burden (related to the caregiving task; see meta analysis and review Gérain & Zech, 2020; Adelman, Tmanova, Delgado, Dion, & Lachs, 2014), and depression (Collins & Kishita, 2020a; de Zwart, Bakx, & van Doorslaer, 2017). The role of a caregiver, which requires time and resources (Bom, Bakx, Schut, & Van Doorslaer, 2019; Pearlin et al., 1990; Revenson et al., 2016c), can limit informal caregivers from receiving professional mental and physical health support for themselves. This is a substantial psychological factor as caregivers struggle with managing stress and practical demands of the caregiving role while experiencing loss (of a person in terms of the care recipient "former self", or of their independence) and not receiving the necessary help (Brodaty & Donkin, 2009; Gérain & Zech, 2019; Revenson et al., 2016a). Above all, due to the loss of a healthy and independent significant other, increased care and family responsibilities, shrinking personal space and reduced social engagement, informal caregivers often report experiencing a tremendous sense of loneliness, which can further impact their ability to self-disclose their emotions and needs to others (Grycuk et al., 2022; Hajek, Kretzler, & König, 2021; Vasileiou et al., 2017; Wagner & Brandt, 2015).

Accordingly, here we investigated the potential of using regular conversations with a social robot as an intervention for supporting informal caregivers coping with emotional distress via self-disclosure (towards the robot) over time. Social robots are autonomous machines that interact and communicate with humans or other agents by following social behaviours and rules relevant to their role (Breazeal, 2003). These robotic agents can take on various forms and shapes and are gradually being deployed across various health and well-being settings due to their ability to function autonomously or semi-autonomously in physical and social spaces alongside humans (see Henschel et al., 2021). Social robots are being increasingly studied and introduced in psychosocial health interventions (see N. L. Robinson et al., 2019), including within mental health settings (see Scoglio et al., 2019; Laban, Ben-Zion, & Cross, 2022), rehabilitation settings (Feingold Polak & Tzedek, 2020), and providing much-needed physical and social support across a number of daily life settings (Henschel et al., 2021). Due to social robots' social features (Cross & Ramsey, 2021; Hortensius & Cross, 2018), animate qualities (Cross et al., 2016, 2012) and physical and social embodiment (Hortensius et al., 2018), previous studies provide evidence for how social robots might be useful for encouraging humans to self-disclose information and emotions (e.g., Laban, George, et al., 2021; Laban, Kappas, et al., 2022a) and provide a sense of companionship to individuals (such as informal caregivers) who could use the support of socially-savvy artificial agents (Ruggiero et al., 2022).

Given the importance of self-disclosure for psychological health in general, and how creating opportunities for more self-disclosure holds potential for supporting informal carers coping with the emotional distress that comes with their caregiving role, we are asking:

RQ: To what extent does self-disclosing to a social robot across several sessions over the course of 5 weeks impact informal caregivers' self-disclosure behaviour toward the robot, perceptions of the robot, and their emotional well being and emotion regulation?

To answer this research question, we conducted a mediated long-term online experiment with informal caregivers conversing with a social robot 10 times over 5 weeks about general everyday topics. We used several objective and subjective measures to evaluate the extent of self-disclosure towards the robot, how it was perceived over time, and how it affected informal caregivers' emotional well-being and emotion regulation.

4.2 Theoretical framework and related work

An individual's ability to regulate their emotions requires responding to ongoing demands and stressors when experiencing a range of emotions in a socially acceptable and sufficiently adaptable way to allow and postpone spontaneous emotional reactions when necessary (Koole, 2009; Leventhal et al., 2007). Therefore, while people sometimes adopt emotion regulation strategies that are adaptive (e.g., reappraisal, acceptance, problem-solving, etc.; see Garnefski, Kraaij, & Spinhoven, 2001) and associated with positive outcomes and well-being, they might also adapt maladaptive emotion regulation strategies (e.g., suppression, avoidance of emotions, ruminating, self-blame, etc.; see Garnefski et al., 2001) that are often associated with negative affect and well-being (Gross & John, 2003; Gross & Levenson, 1993; Aldao & Nolen-Hoeksema, 2012; Aldao, Nolen-Hoeksema, & Schweizer, 2010). Hence, the presence of emotional distress in people's lives can positively impact their growth when such distress is overcome with constructive emotion regulation skills, but emotional distress may also impact people's ability to constructively regulate their emotions, increasing their likelihood of using maladaptive strategies that are more prone to inducing emotional distress (Gross & John, 2003; Aldao et al., 2010).

To overcome the challenges and barriers of emotional distress and constructively regulate the impact of emotional distress and other daily stressors, people often engage in various forms of interpersonal communication activities like self-disclosures and social sharing with others (Coan, 2012; Rimé, 2009; Zaki & Williams, 2013). Numerous health advantages have been associated with engaging in different types of self-disclosure, including the ability to provide and receive support and improve mood, and offer a comfortable setting for concealment and sharing feelings (Coan, 2012; Rimé et al., 1991; Rimé, 2009; Zaki & Williams, 2013). Self-disclosure further serves an important evolutionary function of strengthening interpersonal relationships, while also producing a wide variety of health benefits, including helping people to cope with stress and traumatic events through eliciting help and support (Frattaroli, 2006; Frisina et al., 2004; Kennedy-Moore & Watson, 2001). Moreover, self-disclosure appears to play a critical role in successful treatment outcomes (Sloan, 2010) and has a positive impact on mental and physical health (Derlega et al., 1993).

The map of interpersonal regulation by Zaki and Williams (2013) explains that people might use self-disclosure as an intrinsic regulatory process that can have help achieve different goals, which might be response-dependent or independent. When engaging in intrinsic response-dependent regulation, one might self-disclose to a conversation partner when seeking feedback that will support their regulatory attempt, like seeking an emphatic response or confirmation. Previous research stresses that seeking support and concealment via disclosure can have positive effects on people's mood and helps them to cope with emotional events (e.g., Kahn & Hessling, 2001; Nils & Rimé, 2012).

When engaging in intrinsic response-independent regulation via self-disclosing to others, one will seek a channel for disclosure regardless of a potential response or feedback. Accordingly, the mere act of disclosure contains certain psychological components that effects the regulatory success. Previous research highlights the importance of feeling listened, how it might effect different factors of well being like feelings of loneliness (Itzchakov, Weinstein, Saluk, & Amar, 2022) and perceptions of burden (Itzchakov, Weinstein, & Cheshin, 2022). When sharing with others just for the sake of disclosing emotions and feelings, one might be engaged in appraising their own emotions and experiences and damping the intensity of the emotional experience (Zaki & Williams, 2013). This sort of strategy is also known as affect labelling, a simple and implicit emotional regulation technique aimed at explicitly expressing emotions, or in other words - putting feelings into words (Torre & Lieberman, 2018; Lieberman et al., 2016). Accordingly, people use self-disclosure for emotional introspective processes, self-reflecting on their emotional experiences, as well as past behaviours and actions (Tamir & Mitchell, 2012). A similar example is James Pennebaker's writing disclosure paradigm (see Pennebaker, 1997; Pennebaker & Beall, 1986) that helps people to regulate their emotions when writing about their own experiences. These sort of self-disclosure behaviours is found to be highly useful for coping with emotional distress (Torre & Lieberman, 2018; Kircanski et al., 2012; Lieberman et al., 2011; Kross et al., 2016; Lieberman et al., 2016; Tamir & Mitchell, 2012) and is a meaningful act of mindfulness (Creswell et al., 2007).

4.2.1 Self-Disclosure as an Intervention for Informal Caregivers

The caregiving situation is considered a potential chronic stressor (Pearlin et al., 1990), which has the potential to lead to various negative health and well-being outcomes including strain, burden, and depression (Collins & Kishita, 2020a; de Zwart et al., 2017). Previous empirical findings emphasize that caregiving as a stressor can have serious implications for the caregiver's physical and mental health (Hiel et al., 2015; Pinquart & Sörensen, 2007). Moreover, informal caregivers are at a higher risk of hidden morbidity (Braun, Mikulincer, Rydall, Walsh, & Rodin, 2007; Sambasivam et al., 2019), suffering from a condition without receiving a proper diagnosis, being aware of it or acknowledging one's condition. As informal caregivers struggle in managing to cope with both the stress and the practical demands of the caregiving situation, they often receive no formal mental health treatment or help themselves (Brodaty & Donkin, 2009; Revenson et al., 2016a). While many consider the caregiving role to be rewarding (Zarzycki & Morrison, 2021; Zarzycki et al., 2022), reappraising the caregiving role (i.e., caregiving reappraisal; see Lawton, Kleban, Moss, Rovine, & Glicksman, 1989) negatively can have negative implications to one's emotional well-being. For example, a recently published study suggests that the way informal caregivers reappraise their role is associated with their perceptions of caregiver burden, potentially impacting their burnout rate (Gérain & Zech, 2022).

One issue that is often discussed concerning informal caregivers' emotional distress is their wish for social support and social interaction (Tough, Brinkhof, & Fekete, 2022; Rodakowski, Skidmore, Rogers, & Schulz, 2012). Due to the loss or attenuation of their significant other's health and/or independence, increased care and family responsibilities, shrinking personal space and reduced social engagement, informal caregivers report experiencing a tremendous sense of loneliness that impacts their ability to share their emotions and needs with others (Grycuk et al., 2022; Hajek et al., 2021; Vasileiou et al., 2017; Wagner & Brandt, 2015). Effective interpersonal communication and relations are extremely important for informal caregivers' well-being, positively affecting physical and emotional well-being (S. L. Manne et al., 2006; Northouse et al., 2006; Porter, Keefe, Hurwitz, & Faber, 2005), caregiver burden (Lobchuk & Degner, 2002; S. Manne, Badr, Zaider, Nelson, & Kissane, 2010; Siminoff, Wilson-Genderson, & Baker, 2010), and grief (Schuler et al., 2014).

Previous studies report that interventions designed for dyadic coping via social interaction and social sharing between informal caregivers and their care recipients are often associated with improved psychosocial and health outcomes (Traa, De Vries, Bodenmann, & Den Oudsten, 2015). However, the emotional distress and burdens experienced by informal caregivers can also negatively impact the quality of informal caregivers' relationships with their care recipients (Bjørge, Kvaal, Småstuen, & Ulstein, 2017) and their communication accordingly (Hendriksen et al., 2015; Q. Li & Loke, 2014; McCarthy, 2011; Northouse, 2012) decreasing over time (Song et al., 2012). This may result in caregivers' depression, low patient cohesion and expressiveness and increasing potential for conflicts between the dyads (Siminoff et al., 2010), impacting different forms of burden and also, indirectly, effecting the care recipient's health condition (Savundranayagam, Hummert, & Montgomery, 2005). In fact, a study by Hagedoorn and colleagues (2011) stress that self-disclosure behaviour within dyads of informal caregivers and their care recipients might even be harmful if not reaching equilibrium of reciprocal communication between the dyads (see Derlega et al., 1973; Becker, 1986), and it is recommended that individuals find a supportive other in their social network to confide in.

Due to the emotional distress reported by informal caregivers, they have been found to often engage in suppressive behaviours like protective buffering (Hagedoorn et al., 2000; S. L. Langer, Rudd, & Syrjala, 2007; S. L. Langer, Brown, & Syrjala, 2009) hiding their worries and denying their concerns (S. L. Manne et al., 2006) aiming to protect the care recipients from the information and keeping it to themselves (Caughlin, Mikucki-Enyart, Middleton, Stone, & Brown, 2011; Northouse, Katapodi, Schafenacker, & Weiss, 2012). This maladaptive emotion regulation strategy (suppression; Gross & Levenson, 1993) is associated with negative psychological and health-related outcomes (John & Gross, 2004), negative social outcomes (Butler et al., 2003), and can drastically impact informal caregivers' symptoms of depression and anxiety (Lappalainen, Keinonen, Pakkala, Lappalainen, & Nikander, 2021). There is a limited number of studies that tested interventions for informal caregivers using intrinsic interpersonal emotion regulation techniques for promoting self-disclosure, reducing the potential of suppression (see Gross & Levenson, 1993) and other maladaptive regulatory behaviours. One study describes two randomized controlled trials with informal caregivers (N = 38) going through six structured telephone-based support group meetings (Dichter et al., 2020). Another observational study reported that the presence of friends and social interactions with other people (that are not within the dyad) supports informal caregivers' well-being (Lilly, Richards, & Buckwalter, 2003). A systematic review by Dam and colleagues (2016) explains that there is limited evidence for social support interventions for informal caregivers (via peer support, family support and social network interventions, support groups and remote interventions using the internet or telephone). Nevertheless, a nine-year panel survey reveals that participating in social activities with others (not within the dyad) can effectively reduce informal caregivers' emotional distress (Oshio & Kan, 2016). It is of note that evidence continues to accrue showing that online support groups and social media channels can benefit informal caregivers coping with emotional distress via practising intrinsic (response independent and dependent) regulation techniques, self-disclosing their experiences with the caregiving community (e.g., Benson et al., 2020; Dam, de Vugt, van Boxtel, & Verhey, 2017; Ferrell, Russin, & Hardy, 2019; Kamalpour et al., 2021).

4.2.2 Social Robots for Emotional Support

While numerous therapeutic approaches for supporting and implementing emotion regulation training have been proposed and trialled, (see Mennin & Fresco, 2014), considerable economic, logistical (see Goodwin, Koenen, Hellman, Guardino, & Struening, 2002; Wang et al., 2005), professional (see Thompson, Issakidis, & Hunt, 2008), and socio-emotional barriers (see Corrigan, Druss, & Perlick, 2014) exist that can limit one from receiving appropriate treatment. In the past years numerous emerging technologies have been studied and tested, showing unique opportunities to support emotion regulation in various contexts (Sadka & Antle, 2022; Wadley, Smith, Koval, & Gross, 2020). In a recent scoping review by Sadka and Antle (2022) addressing interactive technologies for emotion regulation training, only one study utilized a social robot for engaging older adults in verbal conversations aimed at detecting and reducing negative affect (see Pham, Do, Su, Bishop, & Sheng, 2021). Nonetheless, social robots hold great potential for delivering or improving psycho-social interventions (N. L. Robinson et al., 2019), supporting mental health (Scoglio et al., 2019), monitoring symptoms of chronic psychopathologies (Laban, Ben-Zion, & Cross, 2022), aiding rehabilitation (Feingold Polak & Tzedek, 2020) and providing much-needed physical and social support across several daily life settings (Henschel et al., 2021).

Due to social robots' social features (Cross & Ramsey, 2021; Hortensius & Cross, 2018), animate qualities (Cross et al., 2016, 2012) and physical and social embodiment (Hortensius et al., 2018), previous studies show how social robots could encourage humans to self-disclose information and emotions (e.g., Laban, George, et al., 2021; Laban, Kappas, et al., 2022a) and provide a sense of companion to individuals like informal caregivers that could use the support of cognitive artificial agents (Ruggiero et al., 2022). Richer modalities of communication like flowing dialogue (see Daft & Lengel, 1986; Carlson & Zmud, 1999) can influence users' perceptions of the system and provide a better user experience than non-interactive systems (e.g., Laban, 2021). Social robots build a sense of rapport (Gratch & Lucas, 2021) by displaying (verbal and nonverbal) social cues (e.g., Laban, George, et al., 2021), while preserving a sense of anonymity (Pickard et al., 2016) which creates a safe and comfortable environment for disclosing emotions (e.g., Nomura et al., 2020; Lucas et al., 2014). Therefore, social robots might just fall at the ideal intersection between being an autonomous and physically present technology (see Henschel et al., 2021) that can capture emotion while also being able to demonstrate social and cognitive cues that might help to respond correctly to those who suffer from emotional distress (Laban, Ben-Zion, & Cross, 2022). Accordingly, many studies show the benefits of employing social robots as alternative self-managed interventions for providing emotional support (Spitale & Gunes, 2022).

For example, in a recent study, a social robot was employed to mediate a single-session loving-kindness meditation and walking meditation, oriented to counter symptoms of depression among young people. The study reports that the social robotic interventions were successful in evoking state openness, with the former also exerting a positive effect on valence (Huang et al., 2022). Several other studies have been addressing long-term interventions for people's well-being, reporting on how these interactive agents might support people in different ways. Bodala and colleagues (2021) employed a social robot delivering teleoperated mindfulness coaching for five weeks. An additional example includes Axelsson and colleagues (2022) that tested a robotic coach conducting positive psychology exercises, showing positive mood change after participation in the robotic intervention. Studies applying robotic interventions for supporting people's emotional distress are rarely taking place in people's homes, and are often conducted in laboratories. One successful example of a field experiment is a study employing the social robot Jibo as a positive psychology coach to improve students' psychological well-being in students' on-campus housing. The study results describe a positive effect on students' psychological well-being with positive mood change, and also students expressing their motivation to change their psychological well-being (Jeong et al., 2022). Another example includes a study by (Spitale, Axelsson, & Gunes, 2023) that employed two robotic coaches of different embodiments (QTrobot with a human/child-like embodiment, and Misty robot with a more machine-like embodiment) for promoting mental well-being in organizational settings. The results of the study indicate that participants perceived the robot Misty more positively than QTrobot and felt a stronger connection with it.

Evidence also exists showing that specific social robot-based interventions can also successfully induce behavioural change, as well as cognitive change. A series of studies by Robinson and colleagues used social robots to deliver behaviour change interventions, applying verbal motivational interventions for reducing high-calorie snack consumption. The studies showed promising results addressing the behavioural change using objective measurements like weight loss (see N. L. Robinson et al., 2020a), and also via qualitative data addressing the subjective experiences of the participants during such interventions (see N. L. Robinson & Kavanagh, 2021). The use of these interventions has demonstrated promising results in patients with diabetes managing their own care for 8 weeks (N. L. Robinson et al., 2020b).

Previous studies stress the potential of employing social robots for supporting intrinsic interpersonal emotion regulation when coping with emotional distress via different forms of self-disclosure. We conducted a mediated long-term online experiment with participants conversing with a social robot 10 times over 5 weeks. We found that people self-disclose increasingly more to a social robot over time, and found the robot to be more social and competent over time. Participants' moods got better after talking to the robot and across sessions, they found the robot's responses to be more comforting over time, and they also reported feeling less lonely over time (Laban, Kappas, et al., 2022a). Another interesting example includes two studies that found that people in bad mood benefited more from disclosing to a robot than participating in writing disclosure using a journal (Duan et al., 2021) or on social media (Luo et al., 2022).

When comparing to disclosures to humans, we previously found that people shared more information with a human than with a humanoid social robot (Laban, George, et al., 2021). Yet, a different study by (Nomura et al., 2020) found that speech interactions with a social robot elicited lower tension compared to interactions with a human agent. The same study (Nomura et al., 2020) showed the benefits of employing social robots for minimising social tension and anxieties, describing that participants with higher social anxiety felt less anxious and demonstrated less tension when knowing that they would interact with a robot as opposed to a human interlocutor.

4.2.3 The current study

With the current study, our aim was to use a social robot-based intervention to elicit rich self-disclosures from informal caregivers via repeated verbal interactions. With this approach, we are hoping to provide a proof of concept for a social robot-assisted intrinsic interpersonal emotion regulation intervention. Following the recommendations of Sadka and Antle (2022) we aspired to use a social robot for providing moments of reflection upon one's emotion regulation skills (via informal caregivers' self-disclosures to the robot), and use a social robot as a technology to leverage social interaction to promote social-emotional communication. Rather than using social robots merely as companions (e.g., Ruggiero et al., 2022), here we employed a social robot for encouraging and listening to people's self-disclosure. By engaging people in self-disclosures to a social robot (or, in other words, talking about themselves and their lives), we expected participants to engage in intrinsic interpersonal emotion regulation (e.g., via affect labelling, Torre & Lieberman, 2018), avoid suppressive behaviours (see Gross & Levenson, 1993) and self reflect on their lives and caregiving experience. Following previous reports about interpersonal emotion regulation (see Zaki & Williams, 2013), we ultimately expect that a social robot could take on the role of an emphatic listener - answering to informal caregivers' needs to socially share and self-disclose their emotions and talk about themselves (Tough et al., 2022; Rodakowski et al., 2012). Due to the caregiving responsibilities, informal caregivers rarely receive a non-judgmental space to conveniently disclose their emotions and needs (Gérain & Zech, 2019), here we aimed to answer this need using an emphatic social robot, even if the robot feedback is not necessary at all (see Zaki & Williams, 2013, Response-Independent Processes). Hence, considering the vast evidence for the positive role of self-disclosure and social sharing in supporting constructive interpersonal emotion regulation, we developed a behavioural paradigm that was aimed at encouraging users to self-disclose to a social robot over time as an intrinsic interpersonal emotion regulation intervention when coping with emotional distress.

We have previously reported the development of the paradigm, the experimental design and procedure, and empirical results from a non informal caregivers sample (Laban, Kappas, et al., 2022a, see a summary of the results in 4.2.2). Following previous recommendations and statements regarding rigorous human–robot interaction (HRI) research and science (Gunes et al., 2022; Henschel et al., 2020, 2021; Cross & Ramsey, 2021), here we replicated the former study (Laban, Kappas, et al., 2022a) with an informal caregiving sample to further validate our previous results, and assess the suitability of this paradigm as a potential intervention to support emotional well-being among a population that is highly prone to emotional distress (Pearlin et al., 1990). We aimed to test the following aspects and achieve the following objectives:

- Due to the negative health outcomes of suppressive coping behaviours (John & Gross, 2004) and the tendency of informal caregivers to engage in such behaviours (see Hagedoorn et al., 2000; S. L. Manne et al., 2006; Caughlin et al., 2011; Northouse et al., 2012) we would like to study how repeated interactions with a social robot affect informal caregivers' self-disclosure behaviour toward the robot. Following our previous results (Laban, Kappas, et al., 2022a) we expect that informal caregivers will gradually open up and self-disclose increasingly more to the robot over time.

- To evaluate the feasibility and adaptation of long-term interactions with social robots as potential interventions for coping with emotional distress we will evaluate informal caregivers' social perceptions of the robot (in terms of mind perception (see H. M. Gray et al., 2007), and friendliness and warmth) and their user experience communicating with the robot over time (in terms of communication competency and interaction quality). Following our previous results (Laban, Kappas, et al., 2022a) we expect that people will gradually perceive the robot as more social and competent over time.

- To further understand the effectiveness of the intervention, and the extent to which self-disclosure to social robots can positively affect informal caregivers' well-being and reduce emotional distress over time, we will evaluate how the repeated interactions with the social robot effects informal caregivers' emotional well-being in terms of their mood, perceiving the robot's responses as comforting, feelings of loneliness and stress, and subjective perceptions of burden from caregiving. In accordance with Laban, Kappas, et al. (2022a), we expect the intervention to have a positive effect on informal caregivers' well-being. Moreover, we would also like to assess the intervention's influence on informal caregivers emotion regulation processes. More specifically, we would like to inspect the extent to which informal caregivers cognitively adapt and change their emotion regulation skills, strategies, and thoughts due to their participation in the intervention.

4.3 Methods

Consistent with previous proposals (Nelson et al., 2012; Simmons et al., 2011), we pre-registered the study and report for how we determined our sample size, all data exclusions, all manipulations and all measures in the study (see Laban, Kappas, et al., 2021b). In addition, following open science initiatives (e.g., Munafò et al., 2017), the de-identified data set, stimuli and analysis code associated with this study are freely available online (see Laban, Kappas, et al., 2020). By making the data available, we enable and encourage others to pursue tests of alternative hypotheses, as well as more exploratory analyses. Since this study almost identically replicated the behavioural paradigm and experimental procedure of Laban, Kappas, et al. (2022a), but with a different participant population, the following methodology section gives a brief summary of these methods, with a particular focus on any differences from the procedure reported by Laban, Kappas, et al. (2022a). For a detailed description of the communication protocol between the participants and the main experimenter (GL), stimuli, and manipulation, please see the relevant sections in Laban, Kappas, et al. (2022a). Preliminary results of the experiment were presented as a poster in the Conference on Human Factors in Computing Systems (CHI) 2022 (see Laban, Morrison, et al., 2022).

4.3.1 Experimental Design

A 10 (chat sessions across time) repeated measures experimental design was followed. Participants conversed with the robot Pepper (SoftBank Robotics) via Zoom video chats about general everyday topics (e.g., social relationships, work-life balance, health and well-being; see section 4.3.4) for 10 sessions. Each interaction consisted of the robot asking the participant 3 questions (x3 repetitions). The topic of each interaction was assigned randomly before the experimental procedure started, as was the order of the questions. Participants were scheduled to interact with the robot twice a week during prearranged times for five weeks.

4.3.2 Participants

Target Population

The target population for this study was exclusively adult (aged 18+) informal caregivers. These are adults from the general population aged 18 or over who are having extra responsibilities looking after a friend or a family member due to a long-term physical or mental ill-health or disability, or problem related to old age (Revenson et al., 2016c). Moreover, participants reported having normal to corrected to normal vision, not suffering from hearing loss or difficulties, or physical handicap, are native English speakers, and currently reside in Great Britain. Due to the technical requirements of the mediated experimental design, the target population of this study consist of individuals with access to a personal computer with Zoom installed, a functioning web camera, a stable internet connection, a microphone, and speakers/headphones.

Recruitment

Participants were recruited via Prolific and were allowed to participate only after confirming that they were older than 18 years, native English speakers, informal caregivers and the main caregiver of their care recipient, residing in the UK, and have access to the technical equipment described above. Also, potential participants (i.e., eligible Prolific users) were asked to commit to attending 2 sessions a week across 5 weeks. Eligible Prolific users could access the Prolific page of the study to receive further information, consider their participation, and complete the induction questionnaire if interested. On the Prolific page of the study (of the induction questionnaire - Session 0) and in the induction questionnaire Qualtrics form, potential participants were introduced to the study, the task, and the available time slots as part of the longitudinal experiment schedule. After receiving this information about the study's requirements, potential participants were then asked if they would like to continue in the study by declaring that they can commit to the study's requirements. Finally, those showing their commitment were then asked to choose their participation time slots, after which they received a participant number to start their participation. Participants were paid a total of £3 for every 30 minutes of participation or participation session if it lasted less than 30 minutes. Participants who completed all 10 sessions were paid an extra £20 after their final interaction. A detailed description of the recruitment procedure and a full list with specific Prolific filters used for participant recruitment can be found on the study's OSF page (see Laban, Kappas, et al., 2020).

Sample

A priori power calculations using G*power software (Faul et al., 2007, 2009) suggest that for reasonable power (0.83) to detect small to medium effect sizes, a sample size of 22 participants would be required. Due to the relatively complex data collection procedure and the potential for a high dropout rate, we recruited 40 participants via the Prolific website. Two participants who were recruited for the study ended up not participating in any of the sessions. Additionally, throughout the study four more participants dropped out, mainly due to their caregiving responsibilities, resulting in a final sample size of 34 participants. Participants were between the ages of 19 and 63 ($M = 39.18$, $SD = 11.44$), 67.6% identify as females, 29.4% identify as males, and 2.9% identify as non-binary/third gender. Half of the sample reports having a Bachelor's degree as their highest level of education, and about a third (32.3%) reports lower educational qualifications. 44.1% are employed full-time, 11.8% employed part time, 23.5% are self-employed, and 20.6% are unemployed. Almost two-thirds (73.5%) of the sample are either married (44.1%) or in a relationship (29.4%). 50% of the sample have at least one child. Most of the participants (94.1%) did not live on their own during their participation in the study, with an average number of 3 individuals (SD = 1.47) in a household (including the participant). 41.2% of the sample consisted of participants who lived with only one additional person in their home other than themselves, and 47.1% of participants reported living with their care recipient. Almost all of the participants (85.3%) did not have previous experience with robots.

Most of the sample (91.2%) reported providing care to only one person, and more than half of the sample (58.8%) provide care to a partner or spouse. Almost 80% (79.4%) of the sample has been providing care for at least 3 years, with 29.4% of the sample reporting providing care for more than 5 years. The most common care recipients' health condition reported is old age and related physical symptoms (e.g., mobility issues) and conditions (e.g., arthritis, osteoporosis) and related mental and cognitive symptoms (e.g., frailty, confusion and memory loss) and conditions (e.g., dementia). Other common conditions reported in the sample are mental health issues (including depression, anxiety, and complex post-traumatic stress disorder), autism, diabetes, heart failure, and cancer. Participants reported an average score of 9.94 (SD = 4.81) in terms of their care recipient functionality, with a minimum score of 1 and a maximum score of 22 (see section 4.3.5). Carer participants reported a high subjective relationship perception score with their care recipient (M = 8, SD = 2.13), and an average of 5.52 (SD = 2.09) in terms of perceived care recipient responsiveness, with a minimum score of 1 and a maximum score of 9 (see section 3.5.2).

Ethics and Communication

Study procedures were approved by the research ethics committee of the University of Glasgow (ethics approval number 300200132). All participants provided written informed consent before participating in the study. Participants were asked to provide, if they wished, optional consent to allow the research team to use their video and audio footage (including videos, audio, and photos made from video material) as materials for research publications, conference presentations, and other multimedia outputs that can and might be disseminated and distributed online, in the media and for public presentations. All Prolific users interested in participating in the study were introduced to the study, the requirements of the study, and the task, but were not informed about the functionalities of the robot Pepper, to ensure all robot knowledge or priming was minimised. During each session (including Session 0), participants were re-introduced to the study, the study's schedule (about their chosen day of participation), and received reminders and information about what the study involves. Furthermore, they were reminded about the benefits and risks of their participation (i.e., ensuring that they would receive their payment, no risks were anticipated as a result of study involvement, and their right to withdraw their participation at any time with no penalty or punishment). Participants were further informed how their data (i.e., behavioural and self-reported data collected in the study) would be used and again reminded of their right to withdraw their data and/or ask that it not be used at any time during or after their participation. Participants were guaranteed that their right to privacy and anonymity would be respected and that no identifiable data would be shared with anyone beyond the research team. Participants were reminded that their participation was voluntary and they were given the contact information of the main researcher and experimenter should they wish to follow up with any further questions. After completing the study, participants received a comprehensive debriefing message in Prolific (forwarded by Prolific to their associated email address), providing further information about the study, the deception that was used (i.e., the experimenter was using the Wizard of Oz (WoZ) approach for communicating with participants to make it look like the robot was responding autonomously), and were again given the contact information of the main experimenter (GL) should they wish to follow up with any further questions or feedback. Further detailed information regarding the communication protocol between the participants and the main experimenter (GL) can be found in Laban, Kappas, et al. (2022a).

4.3.3 Stimuli

Conversational interactions were guided by the robot Pepper (SoftBank Robotics), a humanoid robot capable of communicating via speech and gestures. Following Leite et al. (2013) guidelines for social robots' design for long-term interactions, Pepper was chosen as a suitable robotic platform for this task, given the alignment between Pepper's humanoid embodiment and the social requirements of the conversational task (see Leite et al., 2013, "Guidelines for Future Design"). While Pepper's appearance and behaviours are somewhat human-like (i.e., Pepper has a head, face, torso, two arms, two hands, five fingers per hand, etc.), Pepper has not been designed to resemble a real person. Instead, Pepper's embodiment and behaviours clearly convey human likeness, (further evidenced, for example, by Pepper's abilities to communicate using human speech, but not demonstrating any facial expressions given the rigid, immobile face and head). Pepper was placed in front of a web camera (Logi-tech, 1080p), connected to the experimenter's com-

Figure 4.1: The lab settings, including the robot Pepper (SoftBank Robotics) in front of a web camera, while the experimenter in the back is controlling the robot using the Wizard of Oz technique.

puter (see Figure 4.1). Behind Pepper was a white wall and a flowerpot with a green plant (see Figure 4.2). Pepper communicated with participants in this study via the Wizard -of-Oz (WoZ) technique, controlled by the experimenter via a PC laptop. All pre-scripted questions and speech items were written and coded in the WoZ system, with the experimenter controlling Pepper by pressing buttons on a PC laptop. Accordingly, the procedure followed a clear pre-programmed protocol where the experimenter did not need to speak or type anything during the interaction, but only pressed the relevant keys to trigger the required or appropriate text delivery via Pepper. Further detailed information regarding the stimuli and Pepper's communication capabilities can be found in Laban, Kappas, et al. (2022a).

4.3.4 Manipulation

In accordance with Leite et al. (2013) guidelines for social robots' design for long-term interactions, the interactions followed a clear structure and routine, including the robot performing greetings and farewells, identifying participants by their name, and demonstrating appropriate affective and emphatic responses to participants' answers in order to provide a sense of personal interactions and encourage self-disclosure (see Leite et al., 2013, "Guidelines for Future Design"). Each interaction was guided by Pepper (controlled by the experimenter in a WoZ set up) as a semi-structured interview discussing non-sensitive topics regarding general everyday experiences. Each interaction followed the same order, starting with greetings followed by 3 questions (x3 repetitions). The participants were instructed to have a short conversation with Pepper, following Pepper's lead in the interaction and answering Pepper's questions.The task followed the following structure and order:

- Short greetings/introduction (e.g., Hi there, how are you doing?).
- One pre-defined general question about the participant's day, week, or weekend, to build rapport (e.g., "how was your weekend? Did you do anything interesting?").
- An opening statement introducing the topic of the question (e.g., "I am about to ask you about your social life").
- Two pre-defined, non-sensitive questions that correspond to the topic that was randomly allocated to the interaction (see the questions in table 4.1).

The questions and topics in the study were influenced by Jourard and Lasakow (1958) and Jourard (1971) as an elicitation technique aiming to capture participants' subjective experiences regarding ten everyday topics (Work, Leisure and Passions, Finances, Relationships, Social Life, Mental Health, Physical Health, Personality, Goals and Ambitions, & Routine and Daily Activities; see Laban, Kappas, et al., 2022a). Here we used the same questions from the 'general everyday topics' condition from (Laban, Kappas, et al., 2022a). Further detailed information regarding the manipulation and the task, including the task's structure and content, can be found in Laban, Kappas, et al. (2022a).

4.3.5 Measurements

To ensure that our models only include high-quality data, we included only cases that were captured and processed correctly.

Demographics

Participants were requested to complete a short questionnaire that gathered information on demographic parameters including age, biological sex, gender identification, level of education, nationality, job, previous experience with robots, and whether English is their native language.

Table 4.1: The ten disclosure topics and the corresponding two questions for each topic.

Disclosure Topic	Two Questions
Work	1) What do you do for a living? What do you like the most about your work situation? 2) What do you do for a living? What are the worse aspects of your work situation?
Leisure time and passions	1) What do you do for fun in your spare time? What role does it play in your life? 2) Can you tell me about the things you like the most in the world, and why? For example, a favourite place, music, food, or whatever comes to mind.
Finances	1) How do you feel about your financial situation? 2) Where do you want to be one year from now financially?
Relationships	1) Can you tell me about your closest relationships and the important people in your life? How do these relationships are making you feel 2) Would you mind sharing a memory about your family or your partner? Something that you did together.
Social life	1) Can you tell me about your social-life? How often do you socialize, and how do you feel about it? 2) Would you mind sharing a memory about you and your friends? Something that you did together.
Mental Health	1) How do you emotionally feel? Have you been bothered any time recently by low feelings, stress, or saadness? 2) What do you do to take care of your mental health? What makes you feel better when you are down?
Physical Health	1) How do you physically feel? How does your body affect your daily activities? 2) What are your healthy habits, and the not so healthy habits? Would you like to change some of these habits?
Personality	1) What do you think are your stronger qualities? And what do you think are your weaker qualities? 2) What do you think that other people consider being your strengths and weaknesses?
Goals and Ambitions	1) Would you mind sharing with me what is your most prominent goal or ambition for the near future? 2) Can you think about a meaningful goal or ambition from your past? Did you get to accomplish this goal?
Routine and Daily Activities	1) How does your day usually looks like? What is your daily routine? 2) How do you manage to balance your commitments while investing in yourself? Do you feel that you got it under control?

Information related to the caregiving situation

Questions concerning caregiving-related parameters included the length of time since they started providing care, how many people they provide care to, relationship to the care recipient, whether they live in the same house as their care recipient, their relationship quality with the care recipient, and the health condition of the care recipient. In addition, participants completed two additional scales:

Perceived care recipient responsiveness This twelve item scale assesses how participants experienced and perceived their care recipient responsiveness using an adapted version of the perceived partner responsiveness scale by Reis, Crasta, Rogge, Maniaci, and Carmichael (2017) to the caregiving situation. Each item concerning the informal caregiver perception of the care recipient is scored on a nine-point scale ranging from 1 (not at all true) to 9 (completely true). Accordingly, a mean scale was constructed ($M = 5.52$, $SD = 2.09$) which was found to be reliable (Cronbach's $\alpha = .97$).

Care recipient functionality To assess the care recipient functionality and the intensity of care provided an adjusted version of Lawton's Instrumental Activities of Daily Living (IADL; Graf, 2008) was employed. The scale includes 11 statements addressing different aspects of the care recipient's daily functionality (e.g., taking a bath or a shower, preparing his/her own meals) that can be rated by the caregiver as 0 (without any help), 1 (with some help (person or device)), or 2 (completely unable to perform the task independently). Accordingly, a sum scale was constructed ($M = 9.94$, $SD = 4.81$) which was found to be reliable (Cronbach's $\alpha = .85$).

Disclosure

Subjective self-disclosure Participants were requested to report their level of subjective self-disclosure via an adaptation of the sub-scale of work and studies disclosure in Jourard's Self-Disclosure Questionnaire (1971). This questionnaire was adapted to address disclosure in response to general life experiences, and to the context of the study (i.e., addressing specifically the participants' disclosures to Pepper). The measurement included ten self-reported items for which participants reported the extent to which they disclosed information to Pepper on a scale of one (not at all) to seven (to a great extent). Accordingly, a mean scale was constructed ($M = 3.42$, $SD = 1.19$) which was found to be reliable (Cronbach's $\alpha = .84$).

Disclosure duration Duration of speech in seconds from each recording was extracted and processed using Parselmouth (Jadoul et al., 2018), a Python library for Praat (Boersma & Weenink, 2001).

Disclosure length The volume of disclosure in terms of the number of words per disclosure. The recordings were automatically processed using the IBM Watson speech recognition engine, applying the British telephony model. To ensure capturing all utterances within each disclosure we amplified the audio files with 7 decibels and slowed the audio file's pitch. The number of words per disclosure was extracted from the text using a simple length command in Python.

Perception

Agency and experience Research into mind perception has revealed that agency (the ability of an agent to plan and act) and experience (the ability of the agent to sense and feel) are two key dimensions when valuing an agent's mind (H. M. Gray et al., 2007). To determine whether any differences in mind perception emerged across the testing sessions, participants were requested to evaluate Pepper in terms of agency and experience, after being introduced to these terms (adapted from H. M. Gray et al., 2007). Both concepts were evaluated by the participants using a 0 to 100 rating bar.

Friendliness and warmth The aim of this scale scale is to capture how participants perceived Pepper in terms of friendliness and warmth using one item from Petty and Mirels (1981) and two items from Birnbaum et al. (2016b), as suggested by Ho et al. (2018). These items were evaluated on a seven-point scale ranging from 1 (not at all) to 7 (extremely). Accordingly, a mean scale was constructed (M = 5.92, SD = 1.17) which was found to be reliable (Cronbach's α = .95).

Communication competency This scale was aimed at capturing how participants experienced and evaluated Pepper's communication competency using an adapted and adjusted version by Croes and Antheunis (2020) for a scale by Demeure et al. (2011). The scale included three items that were evaluated on a seven-point scale ranging from 1 (not at all) to 7 (extremely). Accordingly, a mean scale was constructed (M = 5.61, SD = 1.19) which was found to be reliable (Cronbach's α = .92).

Interaction quality This scale was aimed at capturing how participants perceived and evaluated the interaction with Pepper using an adapted and adjusted version by Croes and Antheunis (2020) for a scale by Berry and Hansen (2000).

Each interaction included two random items out of seven, except for the mid-session (session 5) and the last session (session 10) which included all six items of the scale. These items were evaluated on a seven-point scale ranging from 1 (not at all) to 7 (extremely). Accordingly, a mean scale was constructed (M = 5.11, SD = 1.70) which was found to be reliable (Cronbach's α = .96).

Well being

Mood To capture participants' mood change from their interactions with Pepper, participants reported their mood before and after the interaction with Pepper using the Immediate Mood Scaler (IMS-12; see Nahum et al., 2017). IMS-12 includes 12 items of polarized moods, ranging from 1 (for negative moods) to 7 (for the corresponding positive moods). The scale is a novel validated tool based on the Positive and Negative Affect Schedule (PANAS; Crawford & Henry, 2004), adapted and adjusted to capture current mood states in online and mobile experiments (Nahum et al., 2017). Mean reliable scales were constructed for participants' mood before the interaction (M = 4.90, SD = 1.29, Cronbach's α = .97) and after the interaction (M = 5.24, SD = 1.28, Cronbach's α = .98).

Comforting responses To measure the extent to which participants perceived Pepper's responses as comforting the comforting response scale was adapted from R. A. Clark et al. (1998). The scale includes 12 self-reported items rated on a seven-point scale, ranging from 1 (I strongly disagree) to 7 (I strongly agree). Accordingly, a mean scale was constructed (M = 5.12, SD = .82) which was found to be reliable (Cronbach's α = .87).

Loneliness In each session, participants were asked to report their feelings and thoughts of loneliness over the previous three days using the short-form UCLA loneliness scale (ULS-8; see Hays & DiMatteo, 1987). The scale includes 8 items rated on a seven-point scale, ranging from 1 (not at all) to 7 (all the time). Accordingly, a mean scale was constructed (M = 3.10, SD = 1.68) which was found to be reliable (Cronbach's α = .95).

Stress Participants were requested to report their feelings and thoughts of periodic stress from the past month using the perceived stress scale (Cohen et al., 1983). The scale includes 10 statement items rated on a seven-point scale, ranging from 1 (never) to five (very often). A mean scale was constructed (M = 3.74, SD = 1.46) which was found to be reliable (Cronbach's α = .95).

Caregiver burden Participants were requested to evaluate statements addressing burdens associated with the caregiving experience using the short version of the Burden Scale for Family Caregivers (BSFC-s; Graessel, Berth, Lichte, & Grau, 2014). The scale includes 10 items for measuring subjective burden in informal caregivers. Each item is a statement that is rated on a 4-point scale with the values of (0) "strongly disagree", (1) "disagree", (2) "agree", (3) and "strongly agree". A high degree of agreement indicates a higher subjective burden for the caregiver. A sum scale was constructed ($M = 16.63$, $SD = 6.69$) which was found to be reliable (Cronbach's $\alpha = .93$).

Cognitive emotion regulation

In order to assess participants' cognitive change and emotion regulation during the experiment and due to their interactions with Pepper, we used the short version of the Cognitive Emotion Regulation Questionnaire (CERQ-short; Garnefski & Kraaij, 2006) that is based on the original form of the Cognitive Emotion Regulation Questionnaire (CERQ; Garnefski et al., 2001). The questionnaire includes 18 items addressing behaviours and thoughts that convey the practice of nine different strategies of coping and emotional regulation (2 items per technique) evaluated on a five-point scale, ranging from 1 (almost never) to five (almost always). The distinction between the nine strategies includes: Self-blame, Acceptance, Rumination, Positive refocusing, Refocus on planning, Positive reappraisal, Putting into perspective, Catastrophizing and Other-blame. A mean scale was constructed for each strategy, with a high score reflecting high use of the relevant behaviour or thought, with all of the conceptual scales showing good-high reliability except for 'Rumination' (moderate) and 'Refocus on planning' (low) (see table 4.2).

Table 4.2: Mean, standard deviation and reliability scores of the cognitive emotion regulation sub-scales.

Strategy	*M (SD)*	Cronbach's α
Self-Blame	1.87 (1.04)	0.83
Acceptance	4.20 (0.67)	0.76
Rumination	2.96 (0.91)	0.55
Positive refocusing	3.29 (0.95)	0.72
Refocus on planning	3.53 (0.73)	0.10
Positive reappraisal	3.55 (0.87)	0.71
Putting into perspective	3.53 (0.91)	0.70
Catastrophizing	2.40 (1.14)	0.88
Other-blame	2.01 (1.11)	0.89

4.3.6 Materials

Zoom video chat

All interactions (video chats) were conducted with the software Zoom, using a university staff account (see figure 4.2). The interactions were recorded using the recording functionality on Zoom and edited to include only those portions of the recordings where participants and/or Pepper were speaking.

Qualtrics questionnaires

All of the questionnaires were administered via the survey software Qualtrics, using a university staff account. In the online questionnaires, the functionality of recording participants' IP addresses was disabled to comply with GDPR guidelines.

4.3.7 Procedure

When recruited, participants completed an induction questionnaire (Session 0) approximately one week before beginning their video chat interactions with Pepper (Sessions 1 to 10). Participants were instructed to have a short conversation with Pepper about several topics that Pepper will bring up, that Pepper will ask them 3 questions and that the interactions will take place twice a week across five weeks during prearranged times. They were further told that each interaction with Pepper should last about 5 to 10 minutes, and another 10-15 minutes will be required to complete questionnaires afterwards. When answering the induction questionnaire (after providing consent to participate in the study), participants were instructed on how to position their video camera for the video chats, and what the lighting in the room is expected to be like. Following this, participants reported on several demographic parameters and several questionnaires. For the full list of questionnaires and their order in each session see the OSF repository (Laban, Kappas, et al., 2020). Participants were redirected to the Prolific website when completing the induction questionnaire (Session 0). A participant number was automatically generated for each participant who completed the induction questionnaire (Session 0) and proceeded to the following sessions. The random allocation of topics to sessions for each participant and the order of questions in each interaction was randomized and allocated automatically and an excel sheet was created to help the experimenter control and follow the experimental design procedure for five weeks. See the randomization and allocation code, experimenter notebook with the allocated topics to sessions, and order of questions for each of the participants on the OSF repository (Laban, Kappas, et al., 2020).

Figure 4.2: The interaction from the eyes of the participants and the experimenter. The participants were exposed only to the robot Pepper (SoftBank Robotics) via the zoom chats.

When starting each session, participants were asked to enter their Prolific ID and their participant number. Following, participants were asked to answer the Immediate Mood Scale (IMS-12; Nahum et al., 2017) for reporting their mood before interacting with Pepper. Next, participants received a reminder regarding their interaction with Pepper, what the task requires, and some basic instructions. The page included a link to the Zoom interaction, a frame with the zoom landing page, and the experimenter's e-mail address and instructions on how to communicate with the experimenter in case there are any issues during the interaction. Then, participants interacted with Pepper via a Zoom video chat (see section 4.3.4), only seeing Pepper in the chat (see figure 4.2). After finishing their interaction with Pepper, participants went back to the Qualtrics page and answered the rest of the questionnaires. The full list of questionnaires and their order in each session can be found on the study's OSF page (see Laban, Kappas, et al., 2020). When finished answering the questionnaire, participants were thanked for the completion of the session, reminded about the date and day of their upcoming session, were provided again with the contact details of the experimenter, and were directed back to Prolific to receive a completion message. When completing the last session participants were clarified that this is indeed the last session, they were thanked for their participation, and provided with contact details of the experimenter to ask any further questions about the study.

4.4 Results

4.4.1 Disclosure

We used lme4 (Bates et al., 2015) for R to perform a linear mixed effects analysis of the effect of session number on participants' disclosure to Pepper. We entered the

Table 4.3: Results of linear mixed effects analysis of session number effect on participants' disclosure behaviour and perception outcomes.

	Subjective Disclosure		**Duration**		**Length**	
Predictors	*Estimates*	*95%CI*	*Estimates*	*95%CI*	*Estimates*	*95%CI*
Intercept	3.15***	2.78 – 3.52	16.95***	10.48 – 23.43	45.05***	27.49 – 62.61
Session number	0.05***	0.03 – 0.08	2.78***	2.34 – 3.22	6.64***	5.45 – 7.83
Random Effects						
SD	0.99		17.47		47.40	
σ^2	0.46		409.94		2985.92	
τ_{00}	0.97		305.04		2247.18	
ICC	0.68		0.43		0.43	
N	34		34		34	
Observations	333		993		993	
Marginal R^2 / Conditional R^2	0.016 / 0.683		0.082 / 0.474		0.065 / 0.467	

*Note: * p<0.05 ** p<0.01 *** p<0.001*

session order as a fixed effect into the model. As a random effect, we had intercepts for subjects. Significance was calculated using the lmerTest package (Kuznetsova et al., 2017), which applies Satterthwaite's method to estimate degrees of freedom and generate p-values for mixed models.

Subjective self-disclosure

The model explains 68.3% of the variance in participants' subjective self-disclosure, whereas the fixed effect in the model explains 1.6% of the variance. The results stress that despite the variance between the participants (SD = .99), the session number has a significant positive fixed effect on participants' subjective perceptions of their self-disclosures (β = .05, SE = .01, p < .001, see table 4.3). Therefore, participants perceived to be self-disclosing more to the social robot over time (see figure 4.3).

Disclosure duration

The model explains 47.5% of the variance in participants' disclosure duration (in seconds) to Pepper, whereas the fixed effect in the model explains 8.1% of the variance in participants' disclosure duration. The results stress that despite the variance between the participants (SD = 17.63), the session number has a significant positive fixed effect on participants' disclosures duration (β = 2.78, SE = .23, p < .001, see table 4.3). Hence, participants self-disclosed increasingly more (in terms of duration in seconds) to Pepper over time (see figure 4.4).

Another linear mixed effects model was used to test if the session number significantly predicted the disclosure duration when interacting with the social robot Pepper, including only the items corresponding to the disclosure topic. The model explains 60.3% of the variance in participants' disclosures duration (in seconds) to

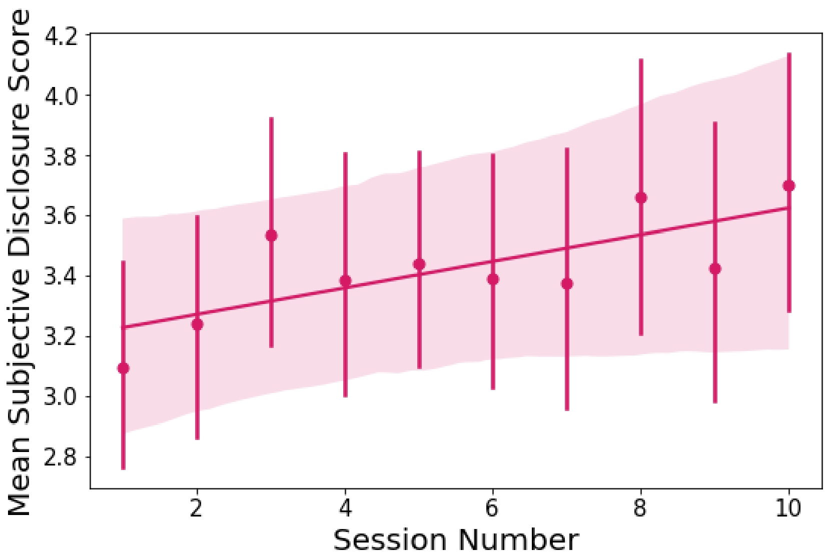

Figure 4.3: Mean subjective disclosure scores (adapted from Jourard, 1971) by session number. The session number has a significant positive fixed effect on participants' subjective perceptions of their self-disclosures. Therefore, participants perceived to be self-disclosing more to the social robot Pepper over time.

Table 4.4: Results of linear mixed effects analysis of session number effect on participants' disclosure behaviour outcomes with only data units corresponding to the disclosure topic.

	Duration		**Length**	
Predictors	*Estimates*	*95%CI*	*Estimates*	*95%CI*
Intercept	20.30***	12.38 – 28.22	53.75***	32.20 – 75.29
Session number	3.42***	2.90 – 3.93	8.18***	6.77 – 9.60
Random Effects				
SD	21.55		58.54	
σ^2	371.54		2802.87	
τ_{00}	464.27		3426.64	
ICC	0.56		0.55	
N	34		34	
Observations	662		662	
Marginal R^2 / Conditional R^2	0.104 / 0.602		0.082 / 0.587	
*Note: * p<0.05 ** p<0.01 *** p<0.001*				

Pepper, whereas the fixed effect in the model explains 10.2% of the variance. The results stress that despite the variance between the participants ($SD = 21.77$), the session number has a significant positive fixed effect on participants' disclosures duration ($\beta = 3.41$, $SE = .26$, $p < .001$, see table 4.4). Therefore, participants self-disclosed increasingly more (in terms of duration in seconds) to Pepper over time (see figure 4.4).

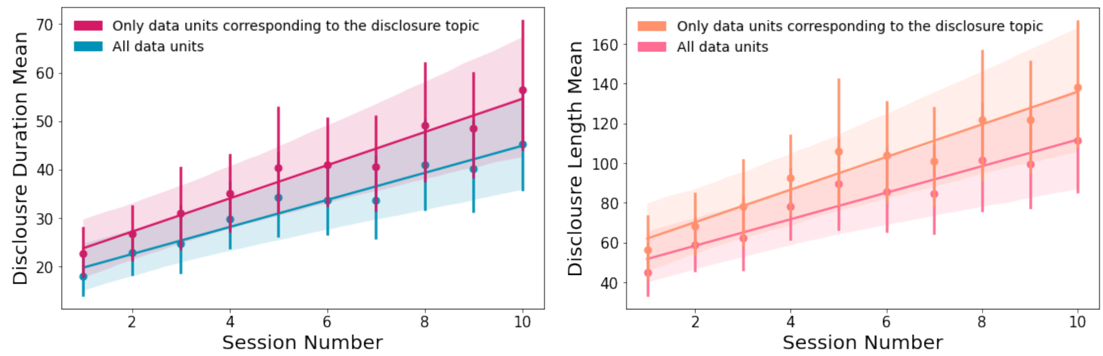

Figure 4.4: From left to right: **(1)** Mean disclosure duration (in seconds) by session number. In navy blue, all data units, in purple, only data units corresponding to the disclosure topic. Both lines indicate that the session number has a significant positive fixed effect on participants' disclosure duration. Hence, participants self-disclosed increasingly more (in terms of duration in seconds) to the social robot Pepper over time. **(2)** Mean disclosure length (in number of words) by session number. In pink, all data units, in orange, only data units corresponding to the disclosure topic. Both lines indicate that the session number has a significant positive fixed effect on participants' disclosure length. Hence, participants self-disclosed increasingly more (in terms of number of words) to the social robot Pepper over time.

Disclosure length

The model explains 46.9% of the variance in participants' disclosures length (in number of words) to Pepper, whereas the fixed effect in the model explains 6.4% of the variance in participants' disclosures length. The results stress that despite the variance between the participants (SD = 47.92), the session number has a significant positive fixed effect on participants' disclosures length ($\beta = 6.63$, $SE = .61$, $p < .001$, see table 4.3). Hence, participants self-disclosed increasingly more (in terms of number of words) to Pepper over time (see figure 4.4).

Another linear mixed effects model was used to test if the session number significantly predicted the disclosure length when interacting with the social robot Pepper, including only the items corresponding to the disclosure topic. The model explains 58.9% of the variance in participants' disclosures length (in number of words) to Pepper, whereas the fixed effects in the model explain 8% of the variance. The results stress that despite the variance between participants (SD = 59.21), session number has a significant positive fixed effect on participants' disclosures length ($\beta = 8.17$, $SE = .73$, $p < .001$, see table 4.4). Hence, participants self-disclosed increasingly more (in terms of number of words) to Pepper over time (see figure 4.4).

Table 4.5: Results of linear mixed effects analysis of session number effect on participants' social perceptions of Pepper.

	Agency		Experience		Friendliness and Warmth	
Fixed Effects	*Estimates*	*95%CI*	*Estimates*	*95%CI*	*Estimates*	*95%CI*
Intercept	59.06***	50.73 – 67.40	53.42***	44.73 – 62.10	5.56***	5.18 – 5.93
Session number	1.03***	0.62 – 1.45	1.67***	1.20 – 2.13	0.07***	0.05 – 0.08
Random Effects						
SD	23.52		24.29		1.07	
σ^2	120.24		152.73		0.20	
τ_{00}	553.28		590.05		1.14	
ICC	0.82		0.79		0.85	
N	34		34		34	
Observations	333		333		333	
Marginal R^2 / Conditional R^2	0.013 / 0.824		0.030 / 0.801		0.026 / 0.852	
*Note: * p <0.05 ** p <0.01 *** p <0.001*						

4.4.2 Perception

We used lme4 (Bates et al., 2015) for R to perform linear mixed effects analysis of the effect of session number on participants' perceptions of Pepper, including perceptions of agency and experience (see H. M. Gray et al., 2007), friendliness and warmth, communication competency and interaction quality. We entered the session order as a fixed effect. As a random effect, we had intercepts for subjects. Significance was calculated using the lmerTest package (Kuznetsova et al., 2017), which applies Satterthwaite's method to estimate degrees of freedom and generate p-values for mixed models.

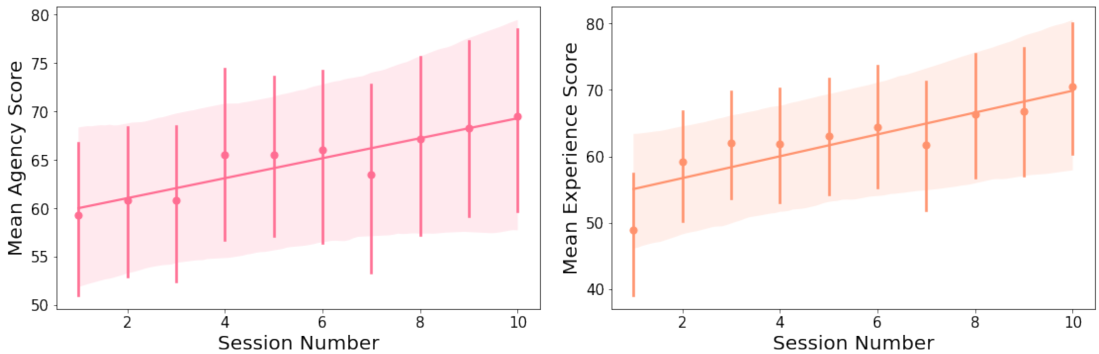

Figure 4.5: From left to right: **(1)** Mean scores of agency (i.e., the ability of the agent to plan and act; see H. M. Gray et al., 2007) by session number. The session number has a significant positive fixed effect on participants' perceptions of the social robot Pepper's degree of agency. Therefore, participants perceived the social robot Pepper to demonstrate higher degrees of agency over time. **(2)** Mean scores of experience (i.e., the ability of the agent to sense and feel; see H. M. Gray et al., 2007) by session number. The session number has a significant positive fixed effect on participants' perceptions of the social robot Pepper's degree of experience. Therefore, participants perceived the social robot Pepper to demonstrate higher degrees of experience over time.

Agency

The model explains 82.4% of the variance in participants' perceptions of Pepper's degree of agency, whereas the fixed effect in the model explains 1.3% of the variance. The results stress that despite the variance between the participants ($SD =$ 23.52), the session number has a significant positive fixed effect on participants' perceptions of Pepper's degree of agency (β = 1.03, SE = .21 $p <$ .001, see table 4.5). Therefore, participants perceived Pepper to demonstrate higher degrees of agency over time (see figure 4.5).

Experience

The model explains 80.1% of the variance in participants' perceptions of Pepper's degree of experience, whereas the fixed effect in the model explains 3% of the variance. The results stress that despite the variance between the participants (SD = 24.29), the session number has a significant positive fixed effect on participants' perceptions of Pepper's degree of experience (β = 1.67, SE = .24, $p <$ .001, see table 4.5). Therefore, participants perceived Pepper to demonstrate higher degrees of experience over time (see figure 4.5).

Friendliness and warmth

The model explains 85.2% of the variance in participants' perceptions of Pepper's degree of friendliness and warmth, whereas the fixed effect in the model explains 2.6% of the variance. The results stress that despite the variance between the participants (SD = 1.07), the session number has a significant positive fixed effect on participants' perceptions of Pepper's degree of friendliness and warmth (β = .07, SE = .01, $p <$ .001, see table 4.5). Therefore, participants perceived Pepper as friendlier and warmer over time (see figure 4.5).

Communication competence

The model explains 72% of the variance in participants' perceptions of Pepper's communication competence, whereas the fixed effect in the model explains 3.5% of the variance. The results stress that despite the variance between the participants (SD = 1), the session number has a significant positive fixed effect on participants' perceptions of Pepper's communication competence (β = .08, SE = .01, $p <$ .001, see table 4.6). Therefore, participants perceived Pepper's to be more competent over time.

Table 4.6: Results of linear mixed effects analysis of session number effect on participants' usability-related perceptions of Pepper.

	Communication Competency		Interaction Quality	
Fixed Effects	*Estimates*	*95%CI*	*Estimates*	*95%CI*
Intercept	5.19***	4.83 – 5.55	4.56***	4.05 – 5.07
Session number	0.08***	0.05 – 0.10	0.10***	0.06 – 0.14
Random Effects				
SD	0.99		1.36	
σ^2	0.40		0.96	
τ_{00}	0.97		1.85	
ICC	0.71		0.66	
N	34		34	
Observations	333		333	
Marginal R^2 / Conditional R^2	0.035 / 0.720		0.030 / 0.669	
*Note: * p <0.05 ** p <0.01 *** p <0.001*				

Table 4.7: Results of linear mixed effects analysis of session number and mood change on participants' well being.

	Mood		Comforting Responses		Loneliness	
Fixed Effects	*Estimates*	*95%CI*	*Estimates*	*95%CI*	*Estimates*	*95%CI*
Intercept	4.94***	4.54 – 5.35	4.78***	4.53 – 5.03	3.31***	2.77 – 3.85
Session number	-0.01	-0.03 – 0.01	0.06***	0.05 – 0.08	-0.05***	-0.06 – -0.02
Mood change	0.24*	0.05 – 0.43				
Session number * Mood change	0.02	-0.01 – 0.05				
Random Effects						
SD	1.15		0.67		1.57	
σ^2	0.34		0.22		0.37	
τ_{00}	1.32		0.43		2.46	
ICC	0.79		0.66		0.87	
N	34		34		34	
Observations	666		333		367	
Marginal R^2 / Conditional R^2	0.018 / 0.796		0.049 / 0.681		0.007 / 0.871	
*Note: * p<0.05 ** p<0.01 *** p<0.001*						

Interaction quality

The model explains 66.9% of the variance in participants' perceptions of the interaction quality, whereas the fixed effect in the model explains 3% of the variance. The results stress that despite the variance between the participants ($SD = 1.36$), the session number has a significant positive fixed effect on participants' perceptions of the interaction quality ($\beta = .10$, $SE = .02$, $p < .001$, see table 4.6). Hence, participants perceived the interections with Pepper to be of higher quality over time.

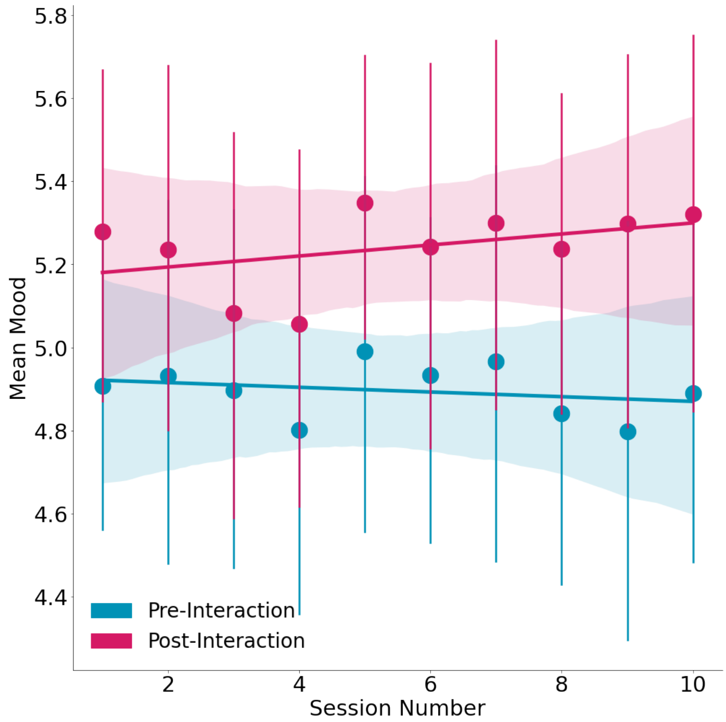

Figure 4.6: Mean mood scores (via IMS-12; see Nahum et al., 2017) of participants before (in navy blue) and after (in purple) the interaction with the social robot Pepper by session number. The results indicate a positive significant fixed effect on mood change, as participants reported a positive mood change after interacting with Pepper. Therefore, participants' mood improved after interacting with Pepper.

4.4.3 Well-being

We used lme4 (Bates et al., 2015) for R to perform a linear mixed effects analysis of the effect of session number on participants' perceptions of Pepper's comforting responses, mood change, feelings of loneliness and stress, and burdens from the caregiving experience. We used session order as a fixed effect in the model. As a random effect, we had intercepts for subjects. Significance was calculated using the lmerTest package (Kuznetsova et al., 2017), which applies Satterthwaite's method to estimate degrees of freedom and generate p-values for mixed models.

Mood

The model explains 79.6% of the variance in participants' mood, whereas the fixed effect in the model explains 1.8% of the variance. The results stress that despite the variance between the participants ($SD = 1.15$), we observed a positive significant fixed effect on mood change, as participants reported a positive mood change after interacting with Pepper ($\beta = .24$, $SE = .01$, $p = .014$, see table 4.7). Therefore, participants' mood improved after interacting with Pepper (see figure 4.6). Nevertheless, there were no significant fixed effects in terms of the session number (β = -.01, SE = .01, p = .479), and the interaction term of mood change and the session number (β = .02, SE = .02, p = .233, see table 4.7).

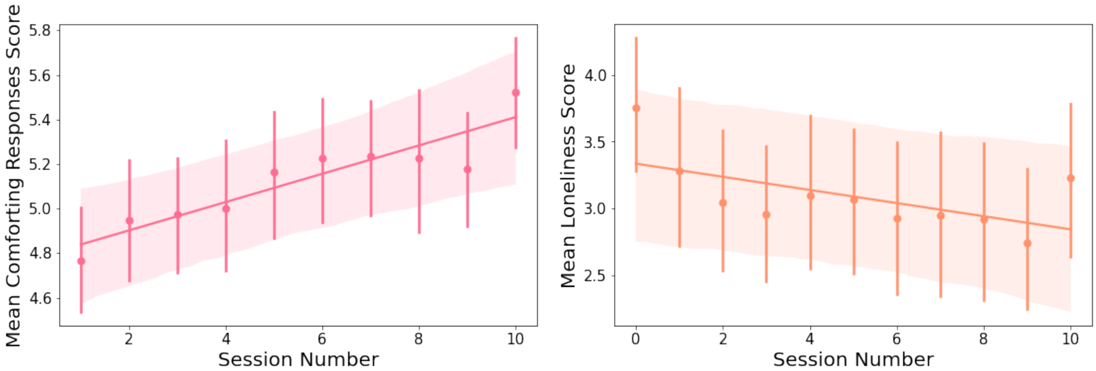

Figure 4.7: From left to right: **(1)** Mean comforting responses scores (adapted from Clark et al., 1998) by session number. The session number has a significant positive fixed effect on participants' perceptions of Pepper's comforting responses. Therefore, participants perceived Pepper's responses to be more comforting over time. **(2)** Mean scores of loneliness (via ULS-8; see Hays & DiMatteo, 1987) by session number. The session number has a significant negative fixed effect on participants' feelings of loneliness. Hence, participants reported feeling less lonely over time.

Comforting responses

The model explains 68.1% of the variance in participants' perceptions of Pepper's comforting responses, whereas the fixed effect in the model explains 4.9% of the variance. The results stress that despite the variance between the participants (SD = .66), the session number has a significant positive fixed effect on participants' perceptions of Pepper's comforting responses (β = .06, SE = .01, p < .001, see table 4.7).Therefore, participants perceived Pepper's responses to be more comforting over time (see figure 4.7).

Loneliness

The model explains 87.1% of the variance in participants' feelings of loneliness, whereas the fixed effect in the model explains 0.7% of the variance. The results stress that despite the variance between the participants (SD = 1.57), the session number has a significant negative fixed effect on participants' feelings of loneliness (β = -.05, SE = .01, p < .001, see table 4.7). Hence, participants reported feeling less lonely over time (see figure 4.7).

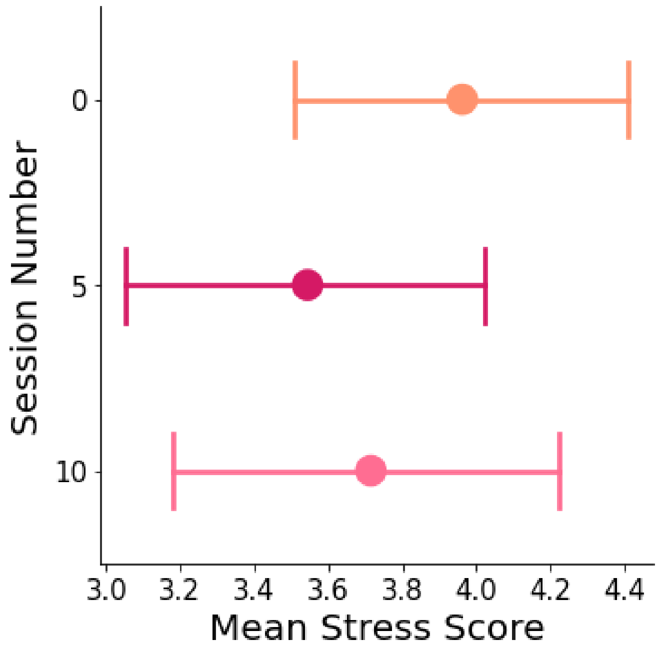

Figure 4.8: Mean stress scores (adapted from Cohen et al., 1983) in sessions 0, 5, and 10. The session number has significant negative fixed effects on participants' feelings of stress in the fifth session compared to the induction session and the last session, and in the last session compared to the induction session and the fifth session. Hence, participants reported feeling less stressed in the fifth session and the tenth session compared to the induction session, which was before engaging in the intervention. As such, the results reflect that participants experienced decreasing feelings of stress over time.

Stress

The model explains 90.9% of the variance in participants' feelings of stress, whereas the fixed effects in the model explain 1.4% of the variance. The results stress that

Table 4.8: Results of linear mixed effects analysis of session number effect on participants' perceived stress.

	Stress	
Fixed Effects	*Estimates*	*95%CI*
Intercept	3.96***	3.47 – 4.46
Session number five	-0.42***	-0.63 – -0.21
Session number ten	-0.24*	-0.45 – -0.02
Random Effects		
SD	1.39	
σ^2	0.19	
τ_{00}	1.92	
ICC	0.91	
N	34	
Observations	101	
Marginal R^2 / Conditional R^2	0.014 / 0.909	
*Note: * p<0.05 ** p<0.01 *** p<0.001*		

despite the variance between the participants ($SD = 1.39$), the session number has significant negative fixed effects on participants' feelings of stress in the fifth session compared to the induction session and the last session (β = -.42, SE = .11, $p <$ .001), and in the last session compared to the induction session and the fifth session (β = -.24, SE = .11, p = .033, see table 4.8). Hence, participants reported feeling less stressed in the fifth session and the tenth session compared to the induction session, which was before engaging in the intervention. As such, the results reflect that participants experienced decreasing feelings of stress over time (see figure 4.8). However, it is important to highlight that while stress seems to decrease over time, the lowest reported stress was mid-study, with no significant differences between perceived stress measured on session 5 and session 10. With only three data points of perceived stress throughout the study (in the induction session, session 5, and the last session), it would be valuable for longer-term interventions to examine the relationship between prolonged interactions with social robots and stress perceptions in more detail, and potentially using objective physiological measures (see Crosswell & Lockwood, 2020).

Caregiver Burden

The model explains 84.5% of the variance in participants' subjective perceptions of burden from their caregiving experience, whereas the fixed effect in the model does not explain any of the variance. The results stress that while considering for the variance between the participants (SD = 6.18), the session number was not found to be a significant predictor for change in participants' perceptions of burden from caregiving. We found no significant difference between participants' burden scores in the induction and the last sessions (β = .23, SE = .65, p = .727). Hence, there is no effect of repeated interactions self disclosing to the social robot Pepper on informal caregiver burden.

4.4.4 Cognitive emotion regulation

We used lme4 (Bates et al., 2015) for R to perform a linear mixed effects analysis of the effect of session number on participants' cognitive emotion regulation strategies, including self-blame, acceptance, putting into perspective, rumination, positive refocusing, positive reappraisal, catastrophizing, blaming others, and refocusing on planning. We used session order as a fixed effect in the model, used as a dummy variable of sessions 0 and 10 whereas 0 is the reference group. As a random effect, we had intercepts for subjects. Significance was calculated using the lmerTest package (Kuznetsova et al., 2017), which applies Satterthwaite's method to estimate degrees of freedom and generate p-values for mixed models.

Table 4.9: Results of linear mixed effects analysis of session number effect on participants' adaptation of cognitive emotion regulation strategies.

Fixed effects of session number on:	*Estimates (SE)*	*p*
Self-Blame	-0.29 (0.17)	0.105
Acceptance	**0.30 (0.13)**	**0.024**
Rumination	-0.22 (0.16)	0.168
Positive refocusing	0.20 (0.15)	0.174
Refocus on planning	-0.10 (0.16)	0.553
Positive reappraisal	**0.30 (0.15)**	**0.045**
Putting into perspective	0.60 (0.15)	0.699
Catastrophizing	-0.19 (0.16)	0.249
Other-blame	**-0.28 (0.14)**	**0.047**

Note: 'Session number' is a dummy variable of sessions 0 and 10 (10 = 1).

We performed 9 models for the 9 strategies. Six of the models do not explain any of the variance in participants' cognitive emotion regulation strategies adaption from session 0 to session 10, including self-blame, rumination, positive refocusing, refocus on planning, putting into perspective, and catastrophizing (see table 4.9). Three of the models provide support to positive adaptation of three of the strategies, including acceptance, positive reappraisal, and other-blame (see table 4.9 and table 4.10).

Acceptance

The model explains 38.5% of the variance in participants' change in acceptance of the caregiving situation from the induction session (session 0) to the last session (session 10), whereas the fixed effect in the model explains 5.3% of the variance. The results stress that despite the variance between the participants (SD = .38), the session number has a significant positive fixed effect on participants' acceptance of the caregiving situation (β = .30, SE = .13, p = .024, see table 4.10). In other words, participants were more accepting of their caregiving situation after participating in the intervention (see figure 4.9).

Positive reappraisal

The model explains 54.6% of the variance in participants' adaption of positive reappraisal of the caregiving situation from the induction session (session 0) to the last session (session 10), whereas the fixed effect in the model explains 3% of the variance. The results stress that despite the variance between the participants (SD = .63), the session number has a significant positive fixed effect on participants' adaption of positive reappraisal of the caregiving situation (β = .30, SE = .15,

Table 4.10: Results of linear mixed effects analysis of session number effect on participants' acceptance, positive reappraisal, and other blame.

	Acceptance		**Positive Reappraisal**		**Other-Blame**	
Fixed Effects	*Estimates*	*95%CI*	*Estimates*	*95%CI*	*Estimates*	*95%CI*
Intercept	4.12***	3.90 – 4.34	3.43***	3.13 – 3.72	2.10***	1.73 – 2.48
Session number	0.30*	0.05 – 0.55	0.30*	0.01 – 0.59	-0.28*	-0.55 – -0.01
Random Effects						
SD	0.38		0.63		0.94	
σ^2	0.27		0.35		0.31	
τ_{00}	0.14		0.40		0.88	
ICC	0.35		0.53		0.74	
N	34		34		34	
Observations	67		67		67	
Marginal R^2 / Conditional R^2	0.053 / 0.385		0.030 / 0.546		0.016 / 0.747	

*Note: * p<0.05 ** p<0.01 *** p<0.001*
'Session number' is a dummy variable of sessions 0 and 10 (10 = 1).

p = .045, see table 4.10). In other words, participants reappraised their caregiving experience more positively after participating in the intervention (see figure 4.9).

Other-blame

The model explains 74.7% of the variance in participants' tendency to blame others for their caregiving situation from the induction session (session 0) to the last session (session 10), whereas the fixed effect in the model explains 1.6% of the variance. The results stress that despite the variance between the participants (SD = .94), the session number has a significant negative fixed effect on participants' tendency to blame others for their caregiving situation (β = -.28, SE = .14, p = .047, see table 4.10). In other words, participants reported experiencing fewer feelings of blame towards others (see figure 4.9).

4.5 Discussion

Here we have introduced a novel long-term mediated intervention aimed at supporting informal caregivers to cope with emotional distress via self-disclosing their emotions and needs to a social robot. This study was a replication of Laban, Kappas, et al. (2022a) with informal caregivers, a population that is normally coping with emotional distress (Pearlin et al., 1990; Revenson et al., 2016a). We were specifically interested in the extent of informal caregivers' self-disclosure behaviour towards the robot over time and how these people's perceptions of the robot developed over time. Moreover, we were interested in how this intervention impacted informal carers' mood, feelings of loneliness, and stress, as well as how it affected their cognitive emotion regulation strategies and thoughts. Participants conversed

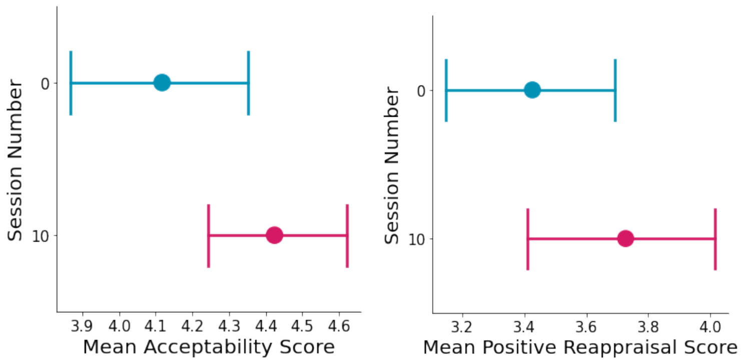

Figure 4.9: From left to right: **(1)** Mean score of acceptance (see Garnefski & Kraaij, 2006) in session 0 and session 10. The session number has a significant positive fixed effect on participants' acceptance of the caregiving situation. In other words, participants were more accepting of their caregiving situation after participating in the intervention. **(2)** Mean score of positive reappraisal (see Garnefski & Kraaij, 2006) in session 0 and session 10. The session number has a significant positive fixed effect on participants' adaption of positive reappraisal of the caregiving situation. In other words, participants reappraised their caregiving experience more positively after participating in the intervention. **(3)** Mean score of other-blame (see Garnefski & Kraaij, 2006) in sessions 0 and 10. The session number has a significant negative fixed effect on participants' tendency to blame others for their caregiving situation. In other words, participants reported experiencing fewer feelings of blame towards others.

with the social robot Pepper 10 times over 5 weeks about general everyday topics. Our results show that informal caregivers self-disclose increasingly more to a social robot over time (in terms of disclosure duration in seconds, and disclosure length in number of words, and also in terms of informal caregivers' subjective perceptions of their own disclosures to Pepper), and perceive the robot as more social and competent over time. Furthermore, we found that informal caregivers' moods positively change after interacting with the robot: they perceive the robot to be more comforting over time, and they feel less lonely and stressed overtime during their participation in the intervention. Finally, our results revealed that after participating in the intervention and self-disclosing to Pepper for 5 weeks, informal caregivers reported being more accepting of their caregiving situation, reappraising it more positively, and experiencing lower feelings of blame towards others.

4.5.1 Robot-led interactions for emotionally distressed individuals

Self-disclosure is a dynamic and socially complex human behaviour (Jourard & Lasakow, 1958; Pearce & Sharp, 1973), and accordingly, the present findings contribute to the understanding of humans' social behaviour and communication with robots. The results of this study complement previous studies addressing humans' social behaviour towards robots in prolonged interactions (e.g., Laban, Kappas, et al., 2022a; N. L. Robinson et al., 2020a), and emphasize how people people open up and socially share with robots. This finding is particularly relevant considering that participants' behaviours in the present study corresponded to their subjective social perceptions of the robot. These findings thus contribute to HRI research and theory by showing users' self-disclosure behavioural changes toward social robots during prolonged and intensive interactions from objective behavioural evidence, as well as from users' self-reported subjective perceptions.

Moreover, the present findings provide compelling evidence for social robots' potential to establish meaningful relationships with human users. While consistent with previous suggestions on the matter (see Fox & Gambino, 2021; Nielsen et al., 2022), the present study provides initial support for long-term relationships between humans users and a social robot, supported with multidimensional data. Our findings establish important foundations for future HRI studies looking into how human–robot relationships develop over time, as well as crucial theory for roboticists trying to create meaningful relationships between their robots and their users. Despite Pepper's limited responses, over time participants attributed more social qualities to this particular robot, thus providing evidence for the influence of social engagement with a robot on its social perception over time. Furthermore, beyond finding Pepper to be more social, participants also attributed higher degrees of competency to Pepper over time. Due to the context of the study and the nature of the task, this provides the research community with substantial evidence for the feasibility and adaptation of social robots as interventions. Nevertheless, the current state of technology is still far from simulating an open dialogue between humans and robots for establishing relationships, but our results here can demonstrate human users' perceptions and behaviours during relationship formation efforts with a social robot. It is important to consider that the interactions in this study were short and restricted to specific limited domains. Accordingly, we can assume that users' expectations of robots are fulfilled when HRIs are aimed at answering specific needs in a specific setting, and therefore, they find the robot to be social and competent over time despite the robot's limitations and limited set of responses.

Finally, considering the positive outcomes on participants well-being due to their disclosures to the robot, these results highlight how human–robot relationships could act as ideal settings for robotic interventions for well-being. These results are particularly interesting due to the unique life situation of this study's target population, informal caregivers (see Revenson et al., 2016c). These individuals are under significant emotional distress and deal with many complex burdens (Revenson et al., 2016a, 2016b; Pearlin et al., 1990). Accordingly, from the results of this study, we can learn about the value of social robot-led interactions with emotionally distressed individuals who might not be suffering from a diagnosed mental condition or illness themselves, but who are living with considerably difficult life situations. Social robots could therefore be used as a tool to facilitate social interactions with emotionally distressed individuals over time, acquire relevant information from their disclosures, and potentially relieve their stress and burden via engaging them in ongoing discussions that elicit rich self-disclosures. We aspire to see more research and development in HRI and social robotics invested into supporting informal caregiversand not only care recipients.

We suspect that while interventions aimed at providing practical assistance (e.g., provision of information about health conditions, care planning, advice about patient management, skills training to aid patient management, stress management training, and problem-solving and decision-making guidance) to informal caregivers to reduce burden (see Beinart, Weinman, Wade, & Brady, 2012) would have a direct effect on informal caregivers' perceptions of caregiving burden, interventions that are oriented towards providing emotional support to informal caregivers (like the one reported in this paper) would have *indirect* (i.e., *mediating*) effect on caregiving burden via caregivers' mood, stress, and other factors related to their emotional well-being. Therefore, despite that our results did not find support for the intervention affecting perceptions of caregiving burden, we would like to encourage further investigation of how interpersonal regulation interventions with social robots and other emerging technologies can support the feelings of burden among caregivers due to the tremendous effect it has on informal caregivers' life and well-being (see Adelman et al., 2014; Gérain & Zech, 2020).

4.5.2 Communicating with robots to avoid suppression of self-disclosure

The findings of the study highlight the capacity of social robots to elicit meaningful and rich self-disclosure from people, including informal carers (the participant population for the current study), who are people under a considerable amount of emotional distress. Suppressive behaviour of self-disclosure is maladaptive (John & Gross, 2004), associated with symptoms of depression (Kahn & Garrison, 2009), and might impact informal caregivers' emotional well-being in a variety of ways (Butler et al., 2003). This behaviour is common among informal caregivers (see Hagedoorn et al., 2000; S. L. Manne et al., 2006; Caughlin et al., 2011; Northouse et al., 2012) and can drastically impact an informal caregiver's symptoms of depression and anxiety (Lappalainen et al., 2021). Our results provide objective behavioural evidence for a positive behaviour change in terms of self-disclosure. Throughout the study period, Pepper elicited richer disclosures from the informal caregivers and reduced the potential levels of suppression accordingly.

More explicitly, our results here show the potential of these interactions to reduce suppression via the elicitation of higher rates of self disclosure over time (in terms of quantities, and with the additional support of participants' perceptions of their own disclosures), as higher quantities of self-disclosure is positively associated with more intimate and personal self-disclosure (Barak & Gluck-Ofri, 2007; Pedersen & Breglio, 1968). Nonetheless, our data is currently limited from qualitatively describing the relevancy of participants' disclosures to the caregiving experience and related stressors. The study results are limited from showing that the self-disclosure behaviour practised in this study objectively reduced suppressive behaviour that is related to the emotional distress experienced by informal caregivers. In other words, we do not know if the informal caregivers that participated in this study avoided self disclosing matters that are related to their caregiving experience, and shared with Pepper information that is corresponding to their caregiving experience. However, while we might expect informal caregivers to mention the caregiving experience (or care-related themes in general) when avoiding suppression (c.f., S. L. Langer et al., 2007, 2009), many informal caregivers (or, people who are emotionally distressed in general) would like to be disclosing (and conversing, in general) about variety of matters that are more directly related to their emotions and feelings (that might not be related to the caregivng experience). This is particularly important in the context of informal caregivers, considering that the caregiving experience takes such a big part of their lives (and accordingly, their daily social interactions), and they rarely get to talk about themselves and how they are feeling (Carlander, Sahlberg-Blom, Hellström, & Ternestedt, 2011). These findings provide important evidence for informal caregivers (and emotionally distressed people in general) behaviour during prolonged interactions with social robots, and how it could potentially reduce suppressive regulatory behaviours when being engaged in self-disclosure to a social robot over time.

Due to the size, complexity and richness of the data collected as part of this study (almost 1000 data units of rich disclosures), performing in-depth qualitative assessments of these disclosures is beyond the scope of the current research. We acknowledge the need to analyse the content of these interactions qualitatively to have a deeper understanding of the nature of informal caregivers' self disclosures' to social robot, what sort of information these disclosures consist of (i.e., addressing explicitly the caregiving experience vs. addressing other events in their lives). This will allow us to determine in a more causal fashion whether these sort of interactions support informal caregivers to avoid suppression via self disclosing to a social robot. Moreover, addressing these questions using qualitative methods will provide us with additional tools to describe self disclosure beyond quantities and subjectively reported perceptions. We aim to follow up this systematic work with a qualitative analysis for a sample of the interactions, while treating participants self-disclosures in a careful, ethically responsible way (see M. Lee et al., 2022).

4.5.3 Social robots for interpersonal emotion regulation

Beyond avoiding suppression, the results here highlight the potential and effectiveness of self-disclosing to a social robot as a constructive form of interpersonal emotion regulation. As participants were self-disclosing increasingly more to Pepper over time, they also reported that their mood positively changed after their interactions, finding Pepper to be more comforting, and feeling less lonely and stressed over time. In terms of cognitive emotion regulation and cognitive change, informal caregivers reported being more accepting of their caregiving situation, reappraising it more positively, and experiencing lower feelings of blame towards others. These findings provide further valuable evidence for the positive outcomes of employing a social robot as an intervention supporting people's well-being and coping with emotional distress. Our results here add to previous studies (e.g., M. Axelsson et al., 2022; Bodala et al., 2021; Duan et al., 2021; Huang et al., 2022; Luo et al., 2022; Jeong et al., 2022; Nomura et al., 2020) that show the benefits of using robots for emotional support. In addition, these findings contribute to our general understanding of how acts of communication towards a social robot, like self-disclosure and social sharing can improve people's emotional well-being. These findings contribute to the introduction of social robots as conversational partners, and how this type of verbal interaction could support people with emotion regulation by talking about stressors and well-being. Simple tasks, like the one described in the study, are relatively easy to administer automatically in HRIs (by focusing on providing general and broad responses to users' disclosures) but can simulate effective procedures via self-disclosure. Accordingly, social robots can offer meaningful opportunities for self-managed interventions designed to support people's emotional health and well-being.

Our results further help to identify specific cognitive emotion regulation strategies that may be impacted by self-disclosure interactions with social robots. By showing that the cognitive emotion regulation strategies of increased acceptance, positive reappraisal and reduced other-blame were all positively impacted by self-disclosure to a social robot, we have identified specific strategies that may be impacted by this type of intervention. Accordingly, our results here suggest potential applications for social robots in real-world settings, providing crucial evidence and laying foundations for future interpersonal emotion regulation interventions with social robots to take place with informal caregivers and other emotionally distressed individuals.

Reflecting on the map of interpersonal regulation (Zaki & Williams, 2013), our findings provide substantial evidence for the benefits and effectiveness of self-disclosing to a social robot as an intrinsic regulatory process that can be response-dependent or independent. One assumption is that despite Pepper's limited responses, participants found Pepper to be more comforting, and might have been engaged in self-disclosing to Pepper as a form of intrinsic response-dependent regulation. Together with the positive influence the interactions had on participants' emotional well-being and cognitive emotion regulation, we can assume that Pepper's empathic responses supported participants coping efforts to a certain extent. Another assumption can be that due to Pepper's limited responses, participants used the intervention as a platform for intrinsic response-independent regulation. Participants used their interaction with Pepper as a convenient space to share their emotions regardless of Pepper's responses, engaging in a regulatory behaviour that is similar to affect labelling (Torre & Lieberman, 2018) and other emotional introspective processes with users self-reflecting on their emotions and behaviours (Tamir & Mitchell, 2012). These results signify the potential of deploying social robots as listeners and highlight how people respond and behave to these embodied artificial agents when in need to be heard (see Itzchakov, Weinstein, Saluk, & Amar, 2022; Itzchakov, Weinstein, & Cheshin, 2022). This is especially meaningful in the context of informal caregiving as informal caregivers rarely have the opportunity to express their feelings or talk about themselves, while their care recipient is often in the spotlight (Carlander et al., 2011). Here we showed how a relatively simple intervention with a widely available social robot could provide a convenient channel to talk about their own emotions feelings, sharing about themselves and for once not about the care recipient.

It is important to mention that in order to further understand the regulatory mechanisms that underpin any positive impacts brought about by this intervention, we must further inspect the qualitative data we collected, open-ended answers from the participants and our own observations. Furthermore, future researchers are encouraged to further inspect these two regulatory mechanisms in interventions with social robots using experimental procedures, casually explaining whether people use their self-disclosures towards social robots for response-dependent or independent intrinsic regulation.

4.6 Conclusions

These findings pave the way for exploring social robots not only as conversational partners in social contexts but also as potential interventions for supporting people to cope with emotional distress. The study offers vital support for how human–robot relationships could act as ideal settings for robotic interventions for well-being. Through a long-term experiment with a target population experiencing high distress and burden (informal caregivers; Pearlin et al., 1990; Gérain & Zech, 2019), our study provides crucial evidence for the benefits and effectiveness of self-disclosing to social robots as means for intrinsic interpersonal regulation. informal caregivers self-disclose increasingly more to a social robot over time, perceived the robot as more social and competent over time, experienced positive mood change, felt less stressed and lonely, and cope better with the caregiving experience via adapting cognitive emotion regulation skills of acceptance, positive reappraisal, and experiencing lower feelings of blame towards others. The Human–Computer Interaction (HCI) and HRI research fields devote considerable research and development resources to eHealth solutions and health technologies in general for care *recipients*, while scant resources are allocated to eHealth solutions and digital interventions for informal care *givers* (Petrovic & Gaggioli, 2020). Even though they may not have a diagnosed condition, many informal caregivers are dealing with very challenging circumstances in their lives and could benefit from the assistance and support of various digital solutions. Instead of just utilizing social robots as companions (e.g., Ruggiero et al., 2022), our goal was to give informal caregivers a self-managed intervention that allowed them to self-reflect on their lives and the caregiving experience via social interactions and promote social-emotional communication with a robotic emphatic agent. Finally, our study reported here further validates previous results (see Laban, Kappas, et al., 2022a), extends this behavioural paradigm as a potential intervention, and adds up to previous research showing how social robots can emotionally support people in need.

Chapter 5

General Discussion

Through this thesis, I studied the underlying psychological mechanisms of perception and behaviour within human–robot communication and their potential deployment as interventions for emotional well-being. I developed original behavioural paradigms using a multidisciplinary approach adopting methods and techniques from social and cognitive psychology, human factors studies and robotics, open-science practices, and clinical psychology and health studies. Through three empirical chapters (including three lab-based experiments, and two longitudinal online-mediated experiments), I have provided evidence of humans' self-disclosure and communication behaviours to social robots, how social robots are perceived during and due to these interactions, and how, in turn, such interactions between humans and robots affect humans' emotional well-being. Finally, I provided evidence for the feasibility and effectiveness of a human – robot communication paradigm as an intervention for supporting informal caregivers to cope with emotional distress. In this final chapter, I summarise the main thesis findings and discuss the implications and limitations of my work. Furthermore, I reflect on the contribution and challenges of this research approach and suggest some future directions for researchers in the relevant fields.

5.1 Main Findings

5.1.1 The role of robotic embodiment in human – robot communication

In Chapter 2, I investigated the extent to which self-disclosures to social robots differ from disclosures to other agents (i.e., humans and disembodied agents), and the extent to which self-disclosures differ in relation to the agent's embodiment in comparison with the disclosure topics. I conducted three laboratory within-subjects experiments and gathered subjective and objective data to answer my research questions. The experiments yielded several important findings that contribute to our understanding of the role of robotic embodiment in human – robot communication. First, I found that overall disclosure (as a multivariate concept) is affected by the agent's embodiment, and not by the topic of disclosure. Nevertheless, self-disclosure is a complex concept that includes several dimensions (Kreiner & Levi-Belz, 2019) and should be approached accordingly. When looking at different dimensions of self-disclosure, I found that self-disclosure volume (quantities in disclosure duration by second, and disclosure length by the number of words) and expression (the disclosure's prosodic qualities, including the disclosures' vocal pitch, harmonicity, vocal intensity and vocal energy) were mostly affected by the agents' embodiment, while the disclosure's content (the content's compound sentiment and sentimentality, see Chapter 2) was mostly affected by the disclosure's topic. I found further evidence for the role of content in chapter 3 when my results suggested that a more seemingly emotional discussion theme (i.e., framing the discussions between participants and the robot to the Covid-19 pandemic) elicited greater feelings of loneliness and stress. Hence, participants reported feeling lonelier and more stressed when the discussion theme was framed to the Covid-19 pandemic.

The results in Chapter 2 highlight the role of (social) robotic embodiment in human – robot communication interactions. The results clearly and unsurprisingly demonstrate that human embodiment elicits the richest disclosures in terms of the quantity of information shared. When participants spoke to another person (i.e., the human agent in the experiment), their disclosures were longer, in terms of number of words and overall duration, than disclosures to the humanoid robot and the disembodied agent. While participants disclosed the most to the agent that looked most like themselves, there was no evidence that stimulus cues for embodiment influenced differences in disclosure quantity and perception between the humanoid social robot and the disembodied agent. It can be argued that in initial interactions (see Berger & Calabrese, 1975) people might require more substantial information than stimulus cues of (human-like) embodiment to treat an agent as more human-like (Cross et al., 2016). While human embodiment naturally resolves some uncertainties of an agent's behaviour (Berger & Bradac, 1982), it may be the case that varying levels of humanness in artificial embodiment do not conform to these rules. Certain behaviours or actions might provide cues or information that extend from the agent's physical embodiment and can support reasoning, mentalizing, and reacting (K. Gray et al., 2012; Waytz et al., 2010; Epley, Waytz, & Cacioppo, 2007; Epley, Waytz, Akalis, & Cacioppo, 2008; Epley & Waytz, 2010). Such attributes can provide a sense of intentionality and meaning to agents' behaviour and would be in line with how humans interact with each other (Wiese et al., 2017).

Nevertheless, consistent with participants' perceptions of the artificial agents (attributing higher degrees of mind to the humanoid social robot compared to a disembodied (or less embodied) voice assistant, in terms of agency and experience, see H. M. Gray et al., 2007), participants' disclosures to the different agents differed in their vocal expression. These changes correspond to and were likely triggered by unique features of the agent's embodiment. For example, the results of the second and third experiments in chapter 2 provide clear evidence for people's voice being higher (as in vocal pitch) when communicating with the humanoid robot. This could potentially be triggered by the robot's child-like embodiment and high-pitched voice. This (replicated) finding would provide evidence for more complex mechanisms of social perception and behaviour towards robots that are manifested via people's disclosures towards them, such as mimicry and imitation. These are behaviours whereby an individual observes and replicates another's behaviour. In its unconscious form (which might have been the case in this study), it is often referred to as "mirroring" (see Chartrand & Bargh, 1999). This is often an unconscious behaviour that is common during conversations to establish rapport with the mirrored individual, allowing for the two individuals to feel more connected and feel a greater sense of engagement and belonging within the situation. Accordingly, this finding highlights the social response of humans to robots, stressing their efforts to establish rapport and social relationships, especially compared to disembodied agents where participants' voices responded differently. These findings expand on the functionalities of social robots as a social communication medium (Zhao, 2006), and the attributes of embodiment that contribute to the "richness" of the medium (Daft & Lengel, 1986).

5.1.2 Social perception of robots is consistent with humans' behaviour.

Across all three experiments described in Chapter 2, participants perceived that they shared more with the human agent than with a humanoid social robot or a disembodied agent, and analyses of self-disclosure volume corroborated this perception. To explain our own and others' behaviour after an interaction takes place, we analyse and self-explain the situation. Interestingly, we use similar mechanisms when interacting with artificial agents, which highlights their social attributes. When using (rather than interacting) with machines, or objects in general, one's subjective memory might frame the situation differently than they would socially frame an interaction with other human agents. However, the results here stress that we might apply similar judgment to our own behaviour when interacting with artificial agents, as we would when interacting with another human. In both Chapters 3 and 4, I found further evidence for this mechanism, this time in repeated interactions. People's perceptions of their own disclosures, as well as perceptions of the robot and the interactions, corresponded to their self-disclosure behaviour toward the robot over time. This key finding supports previous research showing how people's behaviours aligned with their social perceptions and attitudes towards the robot in single-session interactions (Stower et al., 2022). Here I provided further support for this behavioural mechanism in HRI, and the results from both Chapters (3 & 4) demonstrate how perceptions of robots and behaviours toward robots co-align over time during prolonged interactions.

5.1.3 Establishing meaningful relationships with social robots: Evidence of increasingly social behaviour and perception when interacting with a robot over time

Across Chapters, 3 and 4, I found that people self-disclose increasingly more to social robots over time. Self-disclosure is a dynamic and socially complex human behaviour (Jourard & Lasakow, 1958; Pearce & Sharp, 1973), and accordingly, this key finding contributes to our understanding of humans' social behaviour with robots. While numerous prior studies have exported humans' social behaviour towards robots in single-session studies, our knowledge of how people's behaviours towards robots change or develop over the longer term remains limited in social HRI. Naturally, we recognize that people are different and might adapt different behavioural patterns when conversing with social robots (see Chapter 1). Nonetheless, I showed that people self-disclosed increasingly more to a social robot over time in a systematic fashion even when the potential for such inter-individual differences is considered using a rigorous methodology (i.e., mixed effects models controlling for the random effects of intercepts at the subject's level). This key finding also has important implications for our understanding of humans' social communication with social robots. The results in both chapters signify the extent to which people open up and socially share with robots.

These results are further extended when considering the effect the repeated interactions had on social perceptions of the robot, and perceptions regarding its usability. In Chapters 3 and 4, I found that across the 10 sessions, participants attributed to the robot higher qualities of mind (H. M. Gray et al., 2007), in terms of agency and experience. Likewise, over time, participants found the robot to be friendlier and warmer, as well as finding the robot's communication skills more competent and the interactions with the robot to be of increasingly higher quality. This key finding highlights the extent of people's social perception of robots over time, as well as user experience (i.e., perceiving the robot's competency and usability) over time. Despite the robot's limited responses, over time participants attributed more social qualities to this robot, thus providing evidence for the influence of prolonged social engagement with a robot on its social perception. Furthermore, beyond finding the robot to be more social, participants also attributed higher degrees of competency to the robot over time, stressing how familiarity (from repeated interactions) affects people's perceptions of the robot's performance even though there were no objective changes in the robot's performance.

This is a meaningful contribution to HRI theory, showing that prolonged and intensive interactions with social robots can overcome novelty effects from both behavioural objective evidence and from users' self-reported subjective perceptions. While previous longitudinal studies often report novelty effects in human – machine communication encounters (e.g., Croes & Antheunis, 2020, 2021), the results in both chapters provide evidence for a clear opposing trend, with evidence rooted in people's objective behaviour towards robots and their subjective perceptions of robots. These findings provide valuable evidence for social robots' potential to establish meaningful relationships with human users. Consistent with previous suggestions on the matter (e.g., see Fox & Gambino, 2021; Nielsen et al., 2022), this thesis provides initial support for long-term relationships between human users and a social robot, supported with multidimensional data. Furthermore, my findings here lay important foundations for future HRI studies looking into how human-robot relationships develop over time, as well as for roboticists trying to create meaningful relationships between their robots and their users.

While interpersonal communication and the act of self-disclosure specifically are highly dependent on reciprocity (Derlega et al., 1973), this thesis highlight how people and robots may reach a balanced equilibrium (see Argyle & Dean, 1965) despite robots' limited communication abilities. Following the social exchange theory (Homans, 1958, 1961), the results of this thesis stress how humans engage in self-disclosure to a social robot as a form of social exchange, "trading" typical prosocial behaviours (i.e., self-disclosing their emotions and talking about themselves) for a certain value. This value can be the mere act of listening, stressing how people respond and behave to these unique agents when in need to be heard (e.g., Itzchakov, Weinstein, & Cheshin, 2022; Itzchakov, Weinstein, Saluk, & Amar, 2022). Another example can be the need for empathy (Worthy et al., 1969; Zaki, 2020), with people self-disclosing gradually more to a robot due to the robot's cheerful voice and emphatic responses (with regards to the robot's operational behaviour and design and to participants' evaluations of it over time).

Eventually, it can be concluded that people might need to self-disclose for various reasons (Nils & Rimé, 2012; Rimé, 2009; Rimé et al., 1991, 2020; Worthy et al., 1969; Zaki & Williams, 2013) and therefore different robotic features might answer to that need in a reciprocal way despite lacking in equal-to-human social abilities.

5.1.4 Talking to robots can positively affect people's well-being: Evidence of effective social robotic intervention for supporting emotionally distressed individuals

Following the results of social behaviour and perception of robots, I found that these self-disclosure interactions had some influence on participants' well-being. Across Chapters 3 and 4, I found that participants' moods improved after interacting with the robot, and also across the 10 sessions in Chapter 3. Moreover, across the 10 sessions, participants reported the robot's responses to be more comforting. Finally, I found that over time across the experiments (described in chapters 3 and 4), participants reported feeling significantly less lonely and less stressed (only in Chapter 4). These findings provide further valuable evidence for the positive outcomes of employing a social robot as an intervention supporting people's well-being, and add to previous studies (M. Axelsson et al., 2022; Bodala et al., 2021; Jeong et al., 2022) that show the benefits of using robots for emotional support. Taken together with other results reported in this thesis (i.e., that people self-disclose increasingly more to a social robot over time and that people perceive a robot as more social and competent over time; see Chapter 3 and Chapter 4), this thesis provides crucial evidence for establishing relationships with robots in health and care settings. These findings contribute to the introduction of social robots as conversational partners, and how this type of verbal interaction could support people's emotional well-being by talking about their stressors and daily lives and offering them an alternative channel for disclosure. Simple tasks, like the one described in this thesis (Chapters 3 and 4), are relatively easy to administer automatically in HRIs (by focusing on providing general and broad responses to users' disclosures) but can simulate meaningful effective procedures via self-disclosure that can support people's well-being in familiar settings like their homes or community centres.

Considering the unique timing of collecting the data of Chapter 3 (during the peak of the COVID-19 pandemic while most people were under lockdown policies) and the specialised population of chapter 4's sample (i.e., informal caregivers, individuals that are typically under significant emotional distress and deal with many complex burdens (Pearlin et al., 1990; Revenson et al., 2016c, 2016b, 2016a)), we can learn about the value of social robot-led interactions with emotionally distressed individuals. Individuals who might not be suffering from a diagnosed mental condition or illness but are living with considerably difficult life situations. Social robots could therefore elicit rich interactions with emotionally distressed individuals over time, acquire relevant information from their disclosures, and potentially relieve their stress and burden via engaging them in ongoing discussions that elicit rich self-disclosures.

Finally, the results of the thesis provide valuable evidence for potential applications for social robots in real-world settings, specifically as *interpersonal* emotion regulation strategies, and enablers of *intrapersonal* emotion regulation processes. First, the findings of Chapters 3 and 4 highlight the capacity of social robots to elicit meaningful and rich self-disclosure from people which could be implying for supporting people's emotional expression. Suppressing or repressing self-disclosure is maladaptive (John & Gross, 2004), associated with symptoms of depression (Kahn & Garrison, 2009), and might impact people's emotional well-being in a variety of ways (Butler et al., 2003). Accordingly, by encouraging participants to engage in self-disclosure towards a social robot over a lengthy period of time, this thesis suggests that this sort of intervention with social robots can support individuals to express rather than suppress their emotions, offering them an alternative and convenient channel of disclosure. Then, in chapter 4 I showed that after participating in the intervention and self-disclosing towards the robot for 5 weeks, participants reported being more accepting of their caregiving situation, reappraising it more positively, and experiencing lower feelings of blame towards others. Hence, beyond reducing suppression, the results of this thesis highlight the potential and effectiveness of self-disclosing to a social robot as a constructive form of interpersonal emotion regulation that is not only mechanical and related merely to the behavioural function of disclosure to avoid suppression but also related to one's cognitive change throughout the intervention.

The studies contained in this thesis (especially the one in Chapter 4) helps identify specific cognitive emotion regulation strategies that may be impacted by self-disclosure interactions with social robots. By showing that the cognitive emotion regulation strategies of acceptance, positive reappraisal and other-blame were all positively impacted by self-disclosure to a social robot, I have identified specific strategies that may be impacted by this type of intervention. Reflecting on the map of interpersonal regulation (Zaki & Williams, 2013), the findings here provide substantial evidence for the benefits and effectiveness of self-disclosing to a social robot as an intrinsic regulatory process that can be either response-dependent or independent. One assumption is that despite the robot's limited responses, participants found it to be more comforting, and might have been engaged in self-disclosing to it as a form of intrinsic response-dependent regulation. Thus, we can assume that the robot's empathic responses supported participants coping efforts to a certain extent. Another assumption can be that due to the robot's limited responses, participants used the intervention as a platform for intrinsic response-independent regulation. Participants used their interaction with the robot as a convenient space to share their emotions regardless of the robot's responses, engaging in a regulatory behaviour that is similar to affect labelling (Kircanski et al., 2012; Lieberman et al., 2016; Torre & Lieberman, 2018) and other emotional introspective processes with users self-reflecting on their emotions and behaviours (Tamir & Mitchell, 2012).

5.2 General Contributions

This thesis presents an integrative approach to studying questions in the field of human-robot interaction (HRI) that combines insights from multiple disciplinary perspectives. The research contained in this thesis makes several key contributions to the field, including advances in the methodology of HRI research, efforts to increase research reproducibility in the field, and new findings on human-robot communication. These contributions are summarized below.

5.2.1 Overcoming users' dissonance by limiting interactions' domain (applied contributions)

In the past decade, many social robotics firms have failed due to a variety of reasons (Hoffman, 2019). Many failures can be attributed to challenges encountered when developing and designing successful social robotic agents, in particular the user's dissonance when engaging with social robots (or, as termed by Duffy and Joue (2005), the "social robot paradox"). This dissonance can occur when a person is not sure how to behave or interact with the robot, or, more importantly, when the robot's behaviour or functionality is not in line with the person's expectations or preconceived notions about robots. The idea of robots assisting with every aspect of daily life, as depicted in science fiction, has fuelled our imagination about the possibilities for the future. While these fictional robots continue to be a distant vision, they have influenced our understanding and expectations of what autonomous technology could potentially achieve (Duffy & Joue, 2005; Henschel et al., 2021). In the context of human -– robot communication, users' dissonance can occur due to limited flowing interaction that is not corresponding to users' expectations of social interactions with robots. This could be due to previous exposures to depictions of robots in the media and literature, or due to visual cues in the robots' appearance, like anthropomorphic design, that can call for certain behaviour (Broadbent, 2017).

One way to answer this challenge is by limiting the domains or contexts within which people interact with social robots. By limiting the domain of interactions, the robot's capabilities and behaviours are clearly defined and understood, which helps to prevent misunderstandings or miscommunications (Henschel et al., 2021). Although social robots do not currently have the same level of social capabilities as humans, they can still provide valuable opportunities for social interaction in certain contexts (Cross, Hortensius, & Wykowska, 2019) when introduced in a careful and ethical manner (M. Lee et al., 2022; Villaronga et al., 2018; Wullenkord & Eyssel, 2020) within specific and limited domains that frame users' expectations and the robot's performance. In this thesis (Chapters 2 to 4), I showed how social robots can maintain successful communication (speech-based) interaction with human users despite the robot's limited responses. By limiting the interactions to specific domains, I showed how social robots could be supportive in therapeutic contexts also when the interaction is wordy and requires verbal input from the user. When limited to a restricted domain of interaction users could relate to different features of the robot embodiment (as demonstrated in Chapter 2), responses, and functionality (as demonstrated in Chapters 3 & 4), finding the interactions to be more useful, sustaining it over time, and positively affecting their well-being.

5.2.2 Crucial timing for human – robot communication research

Considering the general vision of social robotics, limiting the scope of interaction is only a temporary solution to users' dissonance when communicating with robots. Social robots, as well as other artificial agents, are often expected to demonstrate high social intelligence and competency and simulate flowing interactions (Broadbent, 2017; Kappas et al., 2020). There are numerous technical challenges that limited social robots from reaching expectations (Bonarini, 2020), including (among many others) difficulties in understanding and processing human language, difficulties generating natural-sounding speech, limited machine learning affecting their learning and adaptation, and limited understanding of the social context features in a language like accents, dialects, or slang. However, In the past few years, we have seen tremendous advancements in large language models, such as the ones developed by OpenAI (e.g., GPT-3; T. Brown et al., 2020). These models have the potential to make significant contributions to HRI research and industry, with particular advancements in human – robot communication interactions that are based on verbal input like the studies in this thesis. These models can be used to develop natural language processing (NLP) systems that enable robots to understand and respond to human language in more sophisticated ways. This will enable robots to interact more effectively with humans and will situate robots in more social contexts potentially communicating information, emotion, and even identity, which is a key goal in HRI research (see Laban, Le Maguer, et al., 2022). Nevertheless, these models also set several ethical concerns and risks (see Bender, Gebru, McMillan-Major, & Shmitchell, 2021) that could translate to communication interactions with social robots when these are guided by large language models (M. Lee et al., 2022). Considering these recent advancements, the findings and methods addressed in this thesis are discussed at a crucial time point of AI advancement and adaptation.

As these models are gradually applied in artificial agents (e.g., Chat GPT by OpenAI, 2022), it becomes increasingly important to further understand humans' psychological mechanisms when communicating with robots. We should understand the factors that influence human – robot communication, in terms of visual stimuli, the context of use, and user characteristics. We should identify opportunities and challenges within communication scenarios before implementing large language models in HRI. More importantly, we should understand the effect of these sorts of interactions on human users, how it might affect their well-being, but also how it might affect them in other terms (e.g., communication quality, learning, and maybe even how it makes them feel about themselves). Studies like those described in this thesis will help us to identify the benefits as well as potential risks of using social robots in communication settings and inform the development of ethical guidelines for their use. Employing social robots in ongoing (or, a single session, as in Chapter 2) verbal communication interactions throughout the studies in this thesis simulated desired applications of social robots, yielding a variety of evidence for people's perceptions and behaviours with these sophisticated agents. These results are crucial at this time stamp as we are now at the intersection of creating social robots that further fulfil their potential to communicate freely. The behavioural paradigms and experimental procedures that were developed for this thesis could be further used and replicated in the future to assess and evaluate future robotic agents and validate the effectiveness of using large language models in different contexts and tasks, including health interventions.

Finally, the data collected for this thesis can be used to develop data-centric robotic behaviour architectures. Developing robotic software using data that was acquired in empirical experiments with social robots will help us to create more accurate models that fit robotic agents better while maximising control over the robustness and quality of the data being used. Moreover, using this approach, when collecting data of human users' perception and behaviour to social robotic stimuli, we could develop robotic agents that operate according to users' expectations, perceptions and behaviours. One example of this thesis's contribution to the creation of data-centric robotic behaviour models is the creation of 5 standard neural network architectures, and a novel architecture, that were created for classifying people's subjective perceptions of their self-disclosure in HRI, human-human, and human-agent interactions (see Powell et al., 2022). These models (and other similar models that use the same approach) conceptually mark small steps towards developing robots that understand people from their subjective point of view by synthesizing available non-intrusive behavioural cues.

5.2.3 Methodological contributions

As a number of others have recently argued (Cross & Ramsey, 2021; Gunes et al., 2022; Henschel et al., 2020, 2021; Irfan et al., 2018), it will be beneficial if HRI researchers can develop novel methodologies that take into account best practices from across the engineering and the social sciences (specifically social and cognitive psychology), while learning from the mistakes and successes of these disciplines. Here I have attempted to take steps toward this call to action through the presentation of novel research paradigms designed to address major theoretical and practical challenges in the field (e.g., the role of embodiment in HRI, long-term HRI, the role of novelty in HRI, as well as how these interactions take place in natural ecologically valid settings, and a clear pathway for replication). Through the present thesis, I aimed to establish experimental methods that researchers from HRI, as well as from a number of related fields, including psychology, psychiatry, social work, anthropology, and computer science, might wish to use to further explore people's perceptions of and behaviour towards social robots in communication interactions. Following open science initiatives and proposals (e.g., Munafò et al., 2017), the empirical research contribution presented within this thesis includes de-identified data sets, pre-registrations, stimuli and analysis code associated with this project, which are freely available online (see Laban, George, et al., 2020; Laban, Kappas, et al., 2020). By making these available, other researchers are enabled and supported to pursue tests of alternative hypotheses, as well as to conduct exploratory analyses.

The behavioural paradigm and experimental methods described in Chapter 2 are designed for traditional HRI laboratory-based experimentation and have been replicated twice (3 experiments in total) providing thresholds and benchmark values for crucial variables in human – robot communication research (e.g., disclosure length, duration, vocal pitch, intensity, etc.). The behavioural paradigm and experimental methods described in Chapters 3 and 4 offer a unique and successful methodology for studying human – robot communication in natural everyday settings during prolonged conversational interactions. These methods have been replicated (two long-term experiments in total), with a sample of the general population and with a sample of informal caregivers, yielding fundamental results for the effect of repeated interactions in human – robot communication. I would argue that the online computer-mediated means of human – robot communication used in this experimental design can overcome some of the challenges and barriers that are related to long-term HRI studies in natural ecologically valid settings (such as the costs associated with sending individual robots home for an extended period of time with participants) and suggest alternative means for conducting rigorous HRI research in people's natural settings.

The effective delivery of long-term user studies has long been a longstanding goal (and a challenge) for HRI and social robotics researchers (see Leite et al., 2013). Of the handful of long-term user studies in real-world environments that have been conducted in the past, these are rarely replicated to demonstrate the robustness of results in a systematic fashion (Belpaeme, 2020b; Henschel et al., 2020). Accordingly, while longitudinal effects of repeated HRIs are being increasingly explored in the HRI research community, such long-term engagement studies, and the findings they produce, still require careful validation and replication (Belpaeme, 2020a). This will ensure the burgeoning fields of HRI and social robotics can sidestep the deeply damaging impacts that the well-publicised replication crises in psychology and neuroscience have wrought (Irfan et al., 2018). Hence, beyond exploring general questions regarding how people engage with a social robot from their home settings and how it supports their well-being, the current thesis also provides a means to further examine the impact of novelty effects, and the impact of long-term social engagement with a robot on behaviour (c.f., Cross, Riddoch, et al., 2019; Hortensius et al., 2022). Furthermore, this study can be replicated and tested with various populations, clinical and healthy, in order to understand how social robots could be introduced in different care settings and as interventions using speech-based interactions. By introducing these novel paradigms in detail here, and documenting results from rigorous empirical studies using this paradigm, I aim to provide tools that I hope will be of use to the HRI research community more broadly, while also assisting with facilitating research rigour and reproducibility (Cross & Ramsey, 2021; Gunes et al., 2022; Henschel et al., 2020, 2021).

5.3 Limitations and future directions

In the following sections, I consider several limitations related to these findings and the current research approach. Finally, several ideas for future directions to address these limitations are provided in each of the sections below.

5.3.1 Using Wizard-of-Oz to simulate robotic genuine behaviour.

Throughout the empirical experiments described in this thesis, I used the Wizard-of-Oz (WoZ) technique. This is a common method in HRI in which a human operator (which was I, for the scope of this thesis) controls the robot's behaviour in real-time, while participants believe they are interacting with an autonomous robot. The technique is often used when a fully autonomous robot is not yet available, or when the goal of the study is to understand how humans interact with robots. However, serious limitations must be considered when using the WoZ technique in HRI research (Riek, 2012). First, since the robot is not actually autonomous, it remains unknown the extent to which results obtained from WoZ studies are generalizable to real-world interactions with autonomous robots. This might also present difficulties in measuring the interaction, as the robot is not fully autonomous it might be harder to accurately measure the interaction and evaluate its performance in a replicable way. Limitations of generalizability and replicability are also related to the human operator, as systematic differences between different human operators (within the study, or between different studies) might affect the study's validity. Furthermore, this might also result in random errors affecting the study's reliability, as human operators are prone to human errors with the potential of human operators making mistakes while controlling the robot. In addition, there can be a certain mismatch between the human and robot behaviour, as the operator may act differently from the robot, which can affect the participants' perception of the robot, thus leading to a mismatch in expectations. Ultimately, the presence of a human operator might have a more pronounced effect on the study due to observer biases (or, more specifically, observer-expectancy effect, see Rosenthal, 1976). The human operator may influence the participants' behaviour or affect the outcome of the study, which can introduce bias to the results. These sorts of limitations might also take a more implicit nature affecting the robot's behaviour due to the extra cognitive load on the human operator. The human operator must control the robot while also paying attention to the participants and the experiment instructions. This can be cognitively demanding, which can affect the human operator's ability to control the robot effectively.

To avoid these limitations and minimise the potential of systematic and random errors, I used several practices in my WoZ technique. First, in all studies, there was only one human operator (myself) to reduce the potential of random and systematic errors due to multiple operators and reduce potential variance between the conducted studies so that they will be more comparable. I used a pre-programmed WoZ platform with a clear flow and standardized structure to minimize confusion and cognitive load during the experiment and turned it into an easy mechanic task. All the questions asked by the robots in all the studies in this thesis followed clear pre-written protocols. Accordingly, I pre-programmed all the robot sentences into the system, including questions and responses, organized these in a clear and explicit way that followed the experiments' structure, and never used free text for the robot's responses. The robot's vocabulary in all studies, including the questions asked and the robot's responses, was limited to these specific pre-scripted sentences. This reduces the variance between autonomous robots and WoZ-operated robots and presents a more accurate depiction of the current state of technology. Moreover, it also reduces the potential for any systematic (between the studies described in this thesis, and between the interactions within the studies) and random errors, with limited vocabulary and limited variance of responses. Following, the order of all pre-scripted questions in all studies were randomized and randomly allocated to agents (in Chapter 2, to either a humanoid social robot, human agent or disembodied conversational agent) or to a session (in Chapters 3 and 4, where 10 discussion topics were randomly allocated to 10 sessions). The randomization took place before running the experiments, and I used an experimenter notebook with clear instructions for which questions/topics needs to be followed in each session and with each participant (in an anonymized way) so that the robotic behaviour in the experiment will be documented and will follow clear protocol rather than human judgment. This was also the logic that guided the robots' responses throughout the studies, with the human operator (myself) following a clear protocol guiding the timing and nature of the response. As mentioned above, the robots had a limited variety of responses that were pre-programmed in the WoZ platform. These responses were general and emphatic in character to fit most of the participants' self-disclosures regardless of the disclosure's message and sentiment (see Chapter 3, section 3.3.3). Beyond all that, all the materials from the studies, including the de-identified datasets, stimuli materials (including the pre-programmed questions and responses), and videos of the robot responses (corresponding to the robot presentation in Chapters 3 and 4) are freely available online for further validation and future studies (see Laban, George, et al., 2020; Laban, Kappas, et al., 2020).

Finally, the use of the WoZ technique also poses certain ethical considerations due to the deception involved and the lack of transparency. The WOZ technique can be opaque to the participants, so they may not be aware that they are interacting with a human operator, which can be an ethical concern. This can be a considerable factor in the context of this thesis, where human participants were instructed to self-disclose to a social robot once (in Chapter 2) or ten times (in Chapters 3 and 4). To address these ethical concerns, I took several actions. First, all studies in this thesis were approved by the research ethics committee of the University of Glasgow and followed the required and most thorough ethical conduct that is regularly practised in social psychology experiments that consist of a certain degree of deception. After completing the studies, participants received a comprehensive debriefing message in person (in Chapter 2) and via email (in Chapters 3 and 4), providing further information about the study, the deception that was used (i.e., the experimenter was using WoZ approach for communicating with participants to make it look like the robot was responding autonomously), and were again given the contact information of the main researcher and experimenter should they wish to follow up with any further questions or feedback.

It should also be mentioned that the use of WoZ in this thesis provided several important benefits. The use of WoZ in this thesis allowed me to adapt a human-centred research approach, focusing on understanding the user in these sorts of interactions rather than building novel agents. It allowed me to test a wide range of interactions and behaviours and explore new innovative ideas that might have been difficult to build from scratch within the time frame of completing a PhD. Most importantly, the use of WoZ allowed me to study human behaviour and perceptions of social robots during communication interactions in a controlled and repeatable manner. By having full control over the actions of the robots used in these studies I could carefully control the stimuli presented to participants and precisely measure their responses. This supported my efforts to draw more accurate and reliable conclusions about human behaviour and perceptions in HRI, avoiding the constraints of current technology and potential unpredictable errors and bugs that might appear in autonomous prolonged interactions. Accordingly, I could retain most of my data units, sustain long-term engagements during longitudinal experiments (in Chapters 3 and 4), and ensure that there are no potential confounds in the collected data.

This calls for future replications of the studies conducted here with automated robotic agents. The protocols and procedures that were created for the studies conducted for this thesis could be used for future research replicating the interactions used here with automated speech protocols. Following the gradually growing advances of speech AI and large language models (see section 5.2.2), new technologies like GPT-3 could be implemented in a robotic agent, guided by the data collected in this thesis to ensure smooth robotic communication with human users. These future interactions could be evaluated using the experimental protocols from this thesis, and results could be compared to further understand the variances in human behaviour and perceptions of automated and WoZ-operated robotic agents.

5.3.2 Using computer-mediated means of communication to study HRI

The COVID-19 pandemic emphasized the usefulness of social robots as an assistive technology, especially during times when infection control measures required people to maintain physical distance from each other (Henschel et al., 2021; Scassellati & Vázquez, 2020; G.-Z. Yang et al., 2020). However, it also affected HRI research during times of social distancing as HRI researchers were limited in their ability to use laboratory facilities, reach potential target populations, and conduct in-person studies. The pandemic forced most individuals (including researchers) to adopt computer-mediated means of communication (CMC) (Choi & Choung, 2021). Accordingly, in the studies described in Chapters 3 and 4, I used CMC to simulate verbal repeated interactions between the robot and the participants. While CMC provided me with an opportunity to continue my PhD research during the peak of the pandemic, it also has several limitations.

First, mediated methods may not accurately replicate the complexity and unpredictability of real-world interactions. The variance in real-world HRIs is somewhat high, and even lab-based studies are somewhat far from reproducing the complexity of genuine HRIs. Therefore, mediated HRI studies might be challenged from achieving this level of realistic interactions. This might limit the study's generalizability to some extent, as results from mediated methods may not be directly applicable to real-world HRI, as the mediated environment may not accurately represent the complexity and diversity of real-world interactions. However, it also provides an opportunity for HRI researchers to have far more control behind the screen and avoid many bugs and complexities that are associated with HRIs in the wild, while participants are still in their natural settings. Another limitation that is related to the CMC application in HRI is the limited sensory input. Both humans and robots require sensory input to socially perceive a communication partner and react accordingly. In mediated interactions, both parties (the robot and the human) may not be able to receive or process all the same sensory input as they would in the real world. This can impact the accuracy and validity of the research findings. Interestingly, my results here suggest that despite this limitation participants found the robot to demonstrate higher social qualities across time, and demonstrated richer behaviours (i.e., self-disclosing more over time) despite the limited sensory input of mediated interactions. It could be (and future studies should further assess that) that people's social perception and behaviour toward robots would be even more pronounced due to richer sensory input in real world interactions (see Daft & Lengel, 1986; Carlson & Zmud, 1999). Interestingly, preliminary work by Honig and Oron-Gilad (2020) suggests that the variance between mediated HRI experiments and their in-person comparable experimental designs is limited. However, I still believe that these limitations should be taken into consideration due to the overarching aim of situating social robots in real-world ecological settings.

Despite these limitations, it is proposed that following the wholesale adaptation to CMC during the pandemic (Choi & Choung, 2021), the current thesis sets forth a means for conducting rigorous and reproducible social robotics research to explore people's engagement with social robot-mediated interactions within their own homes. More generally, this thesis sets the stage for further research exploring online mediated speech-based psychosocial interventions with social robots when public health, cost, or logistical barriers prevent situating a physically embodied robot in users' homes across the long term. The use of mediated methods in this thesis allowed me to reach a vulnerable population (i.e., informal caregivers) that would be limited from participating in in-person studies during the peak of the pandemic (see Chapter 4). This is also relevant for future studies using CMC, as it allows researchers to conduct research with participants who may not be able to physically interact with the robot, such as individuals with mobility impairments or those living in remote locations. This can help to increase the diversity of participants and the generalizability of the findings. CMC methods might also have certain methodological benefits with increased experimental control over the interaction, as researchers can pre-program the robot's actions and responses, and manipulate the virtual environment as necessary. Moreover, mediated studies can provide a greater degree of flexibility in terms of the types of interactions that can be studied. For example, it can allow simulating interactions that are difficult or impossible to replicate in the real world, like advanced WoZ studies, or repeated interactions that require a lot of dedication on behalf of the participant. It could be that the admin, logistics, and costs required for conducting similar studies to the ones described in Chapters 3 and 4 of this thesis would have been substantially higher. This could have further implications in terms of potential sample size and experimental power, and the use of CMC allowed me to reach decent power and sample size in my studies.

In conclusion, the computer-mediated method of human – robot communication used in this thesis may be able to address some of the difficulties and obstacles associated with conducting long-term HRI research in natural, ecologically valid settings, such as the costs of sending robots to participants' homes for an extended period of time. While mediated studies have some inherent limitations, it is still useful tool for HRI researchers to add to their toolbox. Future research is encouraged to use the materials produced for this thesis (and are freely provided in the relevant OSF repositories; see Laban, George, et al., 2020; Laban, Kappas, et al., 2020) to replicate the studies in real-life settings. As HRI researchers are gradually returning to laboratory-based experimentation, the materials and results from these studies could further support human – robot communication research in person. In addition, these sorts of interactions are also encouraged to be replicated in various other public settings, like local community centres, schools, and clinics.

5.3.3 The effect of mediated interactions on perceptions of robotic embodiment

Following the previous limitation addressing the use of CMC for studying HRI, one additional limitation of this thesis pertains to the embodiment perception of the social robot during CMC interactions. Due to the mediated nature of the interactions, participants' perception of Pepper's embodiment and physical presence may have been limited. Conducting the study online enabled us to reach a larger and more diverse sample size, enhancing the external validity of our findings while being cost-effective (J. Li, 2015). This method has proven valuable in generating insights and hypotheses that can later be further examined in real-life settings, enabling a more comprehensive understanding of the topic. Furthermore, while some previous studies claim for the moderating role of physical embodiment (Heerink, Kröse, Evers, & Wielinga, 2007; Kiesler, Powers, Fussell, & Torrey, 2008), recent experimental studies that compared in-person interactions with mediated interactions involving social robots have reported no significant differences in participants' perception and behaviour (Honig & Oron-Gilad, 2020; Gittens & Garnes, 2022). Although online settings may not fully replicate real life interactions with social robots, they provide an initial exploration of the potential effects of long-term interactions and allow us to examine the specific research questions we aimed to investigate. This is particularly significant due to the widespread adoption of CMC during the Covid-19 pandemic, which made online interactions more commonplace and therefore made our experiment more reflective of the prevailing social context (Choi & Choung, 2021). The controlled environment of an online experiment also facilitated consistent conditions across participants and minimized confounding variables, which is essential for drawing reliable conclusions. While our study's outcomes offer significant benchmarks and valuable insights for future investigations conducted in real life situations, they can also provide insights into the significance of robots' physical presence compared to the prolonged mediated interactions observed in our study. To address the limitation of generalizability, future research could incorporate real-life interactions with social robots to validate and extend our findings. By comparing outcomes from online and in-person interactions, researchers can gain insights into how embodiment influences the effectiveness of social robots as conversational partners.

5.3.4 Extending from subjective and behavioural measures

The scope of this thesis was limited to examining people's subjective and behavioural responses to social robots, resulting in a lack of investigation into the cognitive or neuropsychological mechanisms underlying human–robot communication. Researchers have emphasized the value of incorporating knowledge and techniques from social cognition and neuroscience in order to achieve a more comprehensive understanding of HRIs (e.g., see Bossi et al., 2020; Cross, Hortensius, & Wykowska, 2019; Cross, Riddoch, et al., 2019; Henschel et al., 2020, 2021; Hortensius & Cross, 2018; Kompatsiari, Pérez-Osorio, Tommaso, Metta, & Wykowska, 2018; Wiese et al., 2017; Wykowska, Chaminade, & Cheng, 2016). Techniques such as functional magnetic resonance imaging (fMRI), eye-tracking, and electroencephalogram (EEG) have been used to study HRI in a more objective manner (e.g., Cross, Riddoch, et al., 2019; Kompatsiari et al., 2018; Kompatsiari, Ciardo, De Tommaso, & Wykowska, 2019; Rosenthal-von der Pütten et al., 2014; Wykowska et al., 2016). These methods might also provide us with more objective evidence of the effect these sorts of interactions have on people's well-being and will support accurate diagnosis and screening of relevant psychopathologies of target populations. While quantitative measures mainly focus on how we interact with social robots and whether certain manipulations impact those interactions, qualitative approaches can offer insight into the reasons behind individuals' responses to robots (Riddoch & Cross, 2021). This study focused on the extent to which people self-disclose to robots and whether self-disclosure affects their well-being, and I aimed to assess that using quantitative systematic methods. However, there are still many questions that could be explored using qualitative approaches. Future research on human-robot communication could adopt a mixed-methods approach (e.g., Riddoch & Cross, 2021), or a multi-methods approach (e.g., Hortensius et al., 2021) to gain a deeper understanding through neurocognitive, physiological, and qualitative measures.

It is important to mention several important aspects regarding the measures used in this thesis. First, despite the lack of neurocognitive measures, in this thesis, I used a variety of subjective and behavioural measures that provided rich evidence for a variety of perceptions, behaviours, and affect. These measures corresponded well with the experimental designs used in this thesis and provided a parsimonious outlook on human – robot communication (i.e., *"Epistemological Parsimony"* - aiming for the simplest possible theoretical explanation for existing data; see Nolan, 1997; Baker, 2003, 2022). Focusing on these measures allowed me to describe people's perceptions and behaviour towards robots in a multidimensional way, capturing the complex nature of their disclosures while also understanding how it may affect their feelings and well-being. Finally, I collected a lot of data during these studies that will be analysed over time. Most importantly, using a mixed methods approach, I collected qualitative data, including open-ended answers from participants, and observations of the interactions (in Chapters 3 and 4). In the future, these qualitative data units will support answering complex questions about human – robot communication, including the subjective nature of the established relationships and why people self-disclose to robots.

5.3.5 Understanding psychological Mechanisms in human–robot communication

In my doctoral research, I aimed to investigate the underlying psychological mechanisms within human–robot communication and their potential as interventions for emotional well-being. Psychological mechanisms can be defined as the processes or cognitive and emotional mechanisms that mediate the relationship between an individual's thoughts, emotions, and behaviours (Koch & Cratsley, 2020). In the context of my research, understanding these mechanisms is crucial for comprehending how self-disclosure and emotional expression occur in interactions with social robots, as well as how they may impact individuals' perceptions of robots, their behaviour towards robots, and eventually their well-being. While my empirical chapters explored various aspects of human–robot communication and self-disclosure, it is important to acknowledge the limitations of the methods employed. The methods used in my research, such as experimental designs employing speech-based communication interactions and long-term interventions, provide valuable insights but have their constraints. They may not fully capture the intricate nuances of the underlying psychological mechanisms at play. Therefore, future studies could employ a combination of qualitative and quantitative approaches, including in-depth interviews and psychophysiological measures, to gain a more comprehensive understanding of the psychological mechanisms involved in human–robot interactions and their effects on emotional well-being.

5.4 Implications and Considerations

5.4.1 Safety and ethical considerations

The introduction of social robots in social settings, particularly in interactions that involve self-disclosures, raises important safety and ethical considerations. As social robots are gradually being integrated into various social and health contexts, it is crucial to carefully examine the potential downsides and address concerns related to privacy, trust, and the preservation of human connection.

Privacy is a primary concern when individuals engage in self-disclosure interactions with social robots (see Lutz & Tamò-Larrieux, 2021; Lutz, Schöttler, & Hoffmann, 2019). These interactions often involve sharing personal and sensitive information. The empirical findings from this thesis shed light on the privacy implications of self-disclosure to social robots. It is imperative to ensure that the data collected by social robots during these exchanges are handled securely and confidentially. Implementing robust data encryption, storage protocols, and access controls is essential to safeguard users' privacy and prevent unauthorized access to personal information. Additionally, clear guidelines and regulations need to be established to govern the use, storage, and protection of such data, taking into account legal and ethical considerations.

Another ethical consideration is the development of artificial trust and reliance on social robots. The results presented in Chapter 3 and Chapter 4 demonstrate the impact of prolonged and intensive long-term interactions with social robots on self-disclosure behaviour, perceptions of the robot, and factors related to well-being. While social robots can exhibit human-like behaviours and establish rapport with users, it is important to acknowledge that they are still machines and lack genuine emotions and empathy. As discussed in both chapters, overreliance on social robots for emotional support and self-disclosure may lead individuals to neglect or undervalue human connections. Therefore, it is crucial to emphasize that social robots should be seen as complementary tools rather than substitutes for human interaction. Consequently, it is necessary to give more thought to the role of social robots as companions. Future studies should focus on exploring and examining how social robots can improve, foster, and facilitate social connections and emotional well-being. This approach should move beyond merely providing artificial attachment, which could potentially evoke negative emotional consequences.

Transparent communication with users is also an ethical imperative in the introduction of social robots in social settings. The findings discussed in this thesis highlight the importance of clear communication and users' understanding of the capabilities and limitations of social robots. This also reflects on the methodology employed in HRI research. Openly discussing the purpose of data collection, the algorithms used, and the decision-making processes of social robots can foster trust and mitigate concerns related to the ethical use of this emerging technology. Transparent communication helps manage user expectations, prevents potential misunderstandings, and avoids the formation of false beliefs about the nature of the interaction (see Bejarano, Li, Ruijs, & Lu, 2022). Additionally, the potential for unintended consequences and biases in interactions with social robots must be carefully examined (M. Lee et al., 2022). The empirical investigations conducted in this thesis contribute to understanding the underlying psychological mechanisms of perception and behaviour within human–robot communication. The findings emphasize the importance of addressing biases in the design and deployment of social robots, ensuring that they promote inclusivity, diversity, and equal treatment of all users. Thorough research and testing, as discussed throughout the empirical chapters, are necessary to identify and address any biases that may arise.

5.4.2 The downsides of using social robots in social settings

Although the findings of this thesis present compelling evidence regarding the potential of social robots to support emotional well-being and facilitate self-disclosure, it is important to acknowledge the downsides of relying solely on robots in social settings. The empirical chapters of this thesis also shed light on these potential downsides and limitations.

One limitation of social robots is their limited ability to understand and respond to the nuances of human emotions (Henschel et al., 2021). The results discussed in Chapter 2 demonstrate how a social robot's embodiment influences people's disclosures and how these disclosures differ from those made to humans and disembodied agents. Human emotions are often complex and multifaceted, requiring empathy, intuition, and contextual understanding to be effectively addressed (see Izard, 2009). Social robots may struggle to provide the same level of emotional support, empathy, and understanding that humans can offer (Park & Whang, 2022). Thus, there is a risk of individuals receiving superficial or inadequate emotional support from social robots, which may not fully address their needs.

Furthermore, relying solely on social robots for self-disclosure interactions may inadvertently isolate individuals from genuine human connections. The findings presented in Chapter 4 highlight the potential of social robots to elicit self-disclosure among those in-need, particularly among informal caregivers. While social robots can answer some of the needs for social connection and provide a sense of comfort and companionship, they cannot replace the depth of emotional connection and understanding that human relationships can offer (Prescott & Robillard, 2021).

Overreliance on social robots may lead to a reduction in meaningful human interactions, potentially resulting in feelings of loneliness, social disconnection, and a decline in overall well-being. Nevertheless, the findings presented in this thesis do enhance our comprehension of how social robots can address certain social needs for individuals requiring assistance, as long as they are introduced in an ethical and responsible manner and within appropriate contexts. Thus, it is advisable to prioritize the implementation of socially assistive robots in public settings (such as community centres, local care homes, schools, universities, etc.) rather than introducing them directly into users' homes to prevent unregulated emotional attachment.

Additionally, the introduction of social robots in social settings should not contribute to *dehumanization* (see Haslam, 2006). As mentioned throughout this thesis, human touch, nonverbal cues, and the presence of another person can convey a sense of warmth, empathy, and understanding that may be challenging for social robots to replicate (Urakami & Seaborn, 2023; Henschel et al., 2021; Hortensius et al., 2018; Hortensius & Cross, 2018). The absence of these human elements in interactions may lead to a sense of detachment or impersonal experiences, particularly in vulnerable individuals who require genuine human connection.

Finally, social robots might be utilized for eliciting information and even persuade people who are vulnerable or that are in endangered circumstances. Vulnerable populations, including children, and individuals with mental health conditions, disabilities, or trauma histories, require special attention to ensure their well-being, safety, and protection. For example, previous studies found that children, both preschoolers and older children, were willing to share sensitive information with humanoid robots. In one study, preschool children were as comfortable sharing a secret with a robot as they were with an adult (Bethel et al., 2011), while in another study, older children showed few differences in reporting bullying incidents between human and robotic interviewers (Bethel et al., 2016). However, relying on robots for children's self-disclosure presents ethical concerns, as robots lack empathy and understanding. There is also a risk of children disclosing personal information without fully grasping the consequences or having adequate privacy protection. While social robots may offer support and a comfortable space for self-disclosure, it is essential to address the potential downsides and ethical implications. These include the limitations of social robots in understanding the complex emotional needs of vulnerable individuals, the risk of excessive reliance on robotic support without fostering genuine human connections, and the potential for privacy breaches or exploitation. Ethical considerations involve obtaining informed consent, ensuring privacy and confidentiality, providing culturally sensitive and inclusive interactions, addressing power dynamics, and avoiding harm or discrimination. Moreover, engaging multidisciplinary teams of healthcare professionals, psychologists, educators, and representatives from relevant communities is crucial for navigating the responsible and ethical use of social robots in self-disclosure interactions with vulnerable populations.

Careful consideration is also necessary when applying social robots in forensic contexts such as prisons and police custody, particularly for conducting intensive investigations or interviews. The unique challenges and power dynamics involved (see Fisher, Svensson, & Wendel, 1989) require attention when introducing emerging technologies in such settings. While social robots have the potential to offer support and facilitate self-disclosure, it is crucial to address security and privacy concerns within these highly regulated environments. In prisons, ensuring security while encouraging self-disclosure is of utmost importance, necessitating strong measures to safeguard sensitive information. When using social robots in police custody, navigating power dynamics and legal implications is essential. Additionally, ethical considerations arise when employing such technology for eliciting information in these settings, questioning whether autonomous agents conducting investigations align with our current moral standards. Other non-forensic social settings, such as religious confessions, may also encounter heightened sensitivity. For instance, in religious places, preserving the sacred nature of self-disclosure and respecting cultural sensitivities is crucial (see Healey, 1990), which might be compromised if one were to confess to a social robot. Furthermore, the concept of a religious individual confiding in a robot for religious confirmation might not align with our moral standards.

In conclusion, the introduction of social robots in social settings, including interactions involving self-disclosure, necessitates careful consideration of safety and ethical concerns. The empirical findings presented in this thesis provide valuable insights into these considerations. Privacy, trust, transparent communication, and addressing biases are crucial aspects that must be addressed to ensure the responsible deployment of social robots. Moreover, it is essential to recognize the limitations of social robots and the potential downsides of overreliance on this technology, emphasizing the importance of human connections in supporting emotional well-being and facilitating meaningful self-disclosure interactions. By acknowledging these considerations and striking the right balance, social robots can be integrated effectively to enhance emotional well-being while preserving the inherent value of human interactions.

5.4.3 The role of culture in self-disclosure to social robots

The findings from the empirical chapters of this thesis shed light on the dynamics of self-disclosure to social robots and their potential as interventions for emotional well-being. However, it is crucial to consider the role of culture in interpreting and generalizing these results. The participants in this study were based in the UK, with English as their native language, and having a cultural background largely influenced by the British context.

Culture plays a significant role in shaping communication styles, social norms, and expectations regarding self-disclosure. Different cultures may have varying levels of comfort and willingness to disclose personal information to others (Giri, 2006; Y. W. Chen & Nakazawa, 2010), including social robots (see Lim, Rooksby, & Cross, 2021). Cross-cultural studies have shown that individuals from collectivistic cultures, such as East Asian cultures, tend to exhibit lower levels of self-disclosure compared to those from individualistic cultures, such as Western cultures (Markus & Kitayama, 1991). Consequently, the way individuals from different cultural backgrounds engage in self-disclosure to social robots may vary. While the participants in this thesis were predominantly from a Western, English-speaking culture, it is important to acknowledge that self-disclosure behaviours might differ in other cultural contexts (see Korn, Akalin, & Gouveia, 2021; Y. W. Chen & Nakazawa, 2010). Future research should consider conducting comparative studies across different cultures and languages to gain a comprehensive understanding of the cultural nuances and their impact on self-disclosure to social robots.

Moreover, language plays a vital role in communication, affecting the nature and depth of self-disclosure (Lindquist, Satpute, & Gendron, 2015). In this thesis, the interactions between participants and social robots were conducted in English. The self-disclosure patterns of future study participants may be influenced by their cultural and linguistic backgrounds, as language proficiency and linguistic nuances impact the extent to which individuals are comfortable expressing their emotions and personal experiences. Language can shape the availability of words and expressions to convey specific emotions or experiences, potentially influencing the depth and breadth of self-disclosure (Lindquist, Satpute, & Gendron, 2015; Lindquist, MacCormack, & Shablack, 2015).

Considering these factors, it is necessary to recognize the challenges in generalizing the findings of this thesis beyond the cultural and linguistic context of the UK participants. Future studies should aim to include participants from diverse cultural backgrounds, with varying languages, to investigate how cultural norms and linguistic factors influence self-disclosure to social robots. In conclusion, while this thesis provides valuable insights into self-disclosure to social robots in the context of the UK and English-speaking participants, it is important to recognize the potential influence of culture and language. By conducting cross-cultural studies and including participants from different cultural backgrounds and languages, researchers can deepen our understanding of how cultural and linguistic factors shape self-disclosure to social robots. This will enable us to develop social robots that are culturally sensitive and adaptable, facilitating effective and meaningful interactions across diverse populations.

5.4.4 The role of demographic diversity in HRI

In within-subjects experiments, researchers often do not explicitly investigate the effects of participants' demographic parameters on outcome variables. This is because within-subjects designs focus on individual differences within the same group (Salkind, 2010; Charness, Gneezy, & Kuhn, 2012). Instead of directly examining demographic parameters (such as age, gender, or occupation), researchers often use mixed effects models to account for random variance associated with the subject level, as demonstrated in this thesis. By controlling for subject-level random effects in the model, the analysis can control for individual differences that may arise due to factors such as age, gender, or other demographic variables (Gibbons, Hedeker, & Dutoit, 2010).

Nevertheless, a valuable direction for future studies would be to explicitly study the impact of specific demographic parameters in HRIs, while researchers are encouraged to analyze demographic data collected for this thesis (see Laban, Kappas, et al., 2020; Laban, George, et al., 2020). Understanding the role and effect of users' specific demographic parameters is crucial in the field of HRI, particularly in relation to users' self-disclosure to social robots, and introducing these agents as potential interventions. Users' age, identified gender, occupation, education level, and other demographic factors significantly influence the way individuals interact with robots and express their emotions. Firstly, users' age plays a significant role in shaping their expectations and comfort levels when interacting with social robots. Older adults may have different comfort levels and expectations compared to younger generations, which may impact their willingness to self-disclose emotions to a robot (Feingold-Polak et al., 2018; Boumans, van Meulen, Hindriks, Neerincx, & Olde Rikkert, 2019; Zafrani, Nimrod, & Edan, 2023). Similarly, users' identified gender can affect their comfort and willingness to express emotions (see Chaplin, 2015), as gender norms and societal expectations may influence the ways in which individuals perceive and communicate emotions to robots (e.g., Xu, 2019). This is also significant regarding the manner in which users assign gender to robots, which could potentially manifest as a collective social bias (see Nomura, 2017; Suzuki & Nomura, 2022). Occupation and education level also shape individuals' communication patterns and emotional expressions (see Van Kleef & Côté, 2022; Cheshin, 2020; Van Kleef, 2009). People from diverse professional backgrounds and educational levels may have varying degrees of familiarity and comfort with technology, which can affect their willingness to self-disclose emotions to robots (Seaborn, Barbareschi, & Chandra, 2023; Szczepanowski et al., 2020). Understanding these demographic parameters enables designers and researchers to tailor robot behaviors and interaction strategies to individual users, promoting effective and empathetic HRI. Furthermore, this is essential for promoting inclusive and diverse interactions with robots (see Seaborn et al., 2023). By considering users' diverse demographics, developers can create robots that adapt to users' preferences and cultural norms, providing a more personalized, comfortable, and inclusive interaction experience.

5.5 Conclusions

This thesis has explored and identified some of the underlying psychological mechanisms supporting perception and behaviour within human – robot communication and the potential deployment of social robots in interventions for emotional wellbeing. In this thesis, I studied the effects of robotic embodiment, social perception, and self-disclosure in human – robot communication interactions. I presented an integrative approach to studying questions in the field of HRI that combines insights from multiple disciplinary perspectives, such as social and cognitive psychology, human factors studies, robotics, open-science practices, and clinical psychology and health studies.

Through multiple laboratory and field (mediated) experiments and the use of subjective and objective data, this thesis has yielded valuable insights into how people communicate with social robots compared to other agents (such as humans or disembodied agents/ voice assistance), and how such communication to social robots develops and changes over time. Accordingly, the thesis emphasizes how people establish meaningful relationships with social robots over time, with self-disclosure increasing and social perceptions of the robot improving. The results show that self-disclosure to social robots is consistent with human behaviour and that social perception of robots aligns with human behaviour over time. Using a multidisciplinary approach, adopting methods and techniques from computer science, interaction studies, cognitive and health psychology, and embracing open-science practices, my dissertation research has shown that human – robot communication paradigms (i.e., self-disclosing to robots) can effectively support people in difficult life situations (e.g., informal caregivers) to cope with emotional distress.

This thesis demonstrates that talking to robots can positively affect people's mood, comfort, and feelings of loneliness and stress over time. Furthermore, the results of this thesis provide strong evidence for the potential applications of social robots in real-world settings, specifically as interpersonal emotion regulation strategies. By encouraging participants to engage in self-disclosure towards a social robot over a lengthy period of time, this thesis suggests that this sort of intervention with social robots can support individuals to avoid suppressing their emotions, offering them an alternative and convenient channel of disclosure, and positively effecting their emotional well-being over time. Moreover, after participating in a long-term intervention, informal caregivers reported evidence for positive cognitive emotion regulation change, by being more accepting of the caregiving situation, reappraising it more positively, and showing reduced blame for others. The results of this thesis provide a valuable contribution to our understanding of human-robot interactions and the potential for social robots to be used in health and care settings.

This research highlights the potential of social robots in certain contexts and how social robots can engage in successful communication and interaction with human users despite their limited responses, and their potential to maintain it over time. Additionally, beyond presenting new findings on human-robot communication, the thesis has made several key contributions to the field of HRI, including advances in research methodology, efforts to increase reproducibility in the field, and developing and testing novel behavioural paradigms and experimental procedures for human – robot communication. The results of this thesis provide insights for future research and design in human – robot communication and the deployment of such systems for interventions for emotional well-being. Considering recent advancements in large language models, the results and methods presented here set the stage for further exploration to understand the psychological mechanisms behind human – robot communication, particularly before implementing these models in social robots. Studies like the ones described in this thesis can help to identify the benefits and potential risks of using social robots in communication settings and inform the development of ethical guidelines for their use.

Appendix A

Supplementary material for Chapter 3

A.1 Recruitment - full description and filters

Participants were recruited via Prolific and were allowed to participate only after confirming that they were older then 18 years, are native English speakers, and have access to a computer with Zoom installed as well as a decent web camera, stable internet connection, microphone, and speakers/headphones. Also, Prolific users were asked to commit to attending 2 sessions a week across a 5 week period. Specific Prolific filters used for participant recruitment were as follows:

- Native language (being English).
- Age (18+).
- Current country of residence (being the United Kingdom).
- Place of most time spent before turning 18 (being either "In England" or "Elsewhere in the UK").
- Vision (reporting to have normal to corrected to normal vision).
- Hearing difficulties (reporting to not suffer from hearing loss or difficulties).
- Mild cognitive impairment/Dementia (reporting to never being diagnosed with mild cognitive impairment or dementia).
- Mental health/illness/condition - ongoing (reporting to not having or have had in the past a diagnosed, on-going mental health/illness/condition).
- Webcam (reporting to have a webcam or built-in camera and willing to use it as part of the study).

- Video call interview (reporting to be willing to participate in a face to face video call interview).
- Record video (reporting to be willing to be recorded via a webcam as part of a study).
- Participants were limited to complete the study on their desktop computer and could not participate in the study using mobile or tablet devices.

Since a longitudinal study is depended on participants' cooperation, the following filters were also applied in Prolific:

- Prolific tasks' approval rate (between 80% to 100%).
- Number of previous submissions on Prolific (at least 15 completed submissions on Prolific).

After applying these filters, 4424 matching eligible Prolific users had been active in the past 90 days before starting the recruitment procedure, on Friday, 19/02/2021. Eligible Prolific users could access the Prolific page of the study to receive further information, consider their participation, and complete the induction questionnaire if interested. On the Prolific page of the study (of the induction questionnaire - Session 0) and in the induction questionnaire Qualtrics form, Prolific users were introduced to the study, the task, and the available time slots as part of the longitudinal experiment schedule. After receiving this information about the study's requirements, Prolific users were then asked if they would like to continue in the study by declaring that they can commit to the study's requirements. Following this, Prolific users were asked to sign a participant consent form. Prolific user then were asked to provide, if they wished, optional consent to allow the research team to use their video and audio footage (including videos, audios, and photos made from video material) as materials for research publications, conference presentations, and other multimedia outputs that can and might be disseminated and distributed online, in the media and for public presentations. Finally, Prolific users were then asked to choose their participation time slots, after which they received a participant number to start their participation. They were then immediate able to begin answering the induction questionnaire (Session 0).

Participants were paid a total of £3 for every 30 minutes of participation or participation session if it lasted less than 30 minutes. Participants who completed all 10 sessions were paid an extra £20 after their final interaction. From the 4424 matching eligible Prolific users on Prolific, 40 participants were recruited on Friday, 19/02/2021, to start their participation by completing an induction questionnaire (Session 0) using a Qualtrics form. After completing the induction questionnaire, the last page of the form reminded participants of their participation time slot and day, and the date for their first session in the experimental procedure (Session 1) after the induction session (Session 0). The first interaction with the social robot as part of the experiment (Session 1) took place on Thursday, 25/02/21, for those who scheduled their sessions on Mondays and Thursdays, and on Friday, 26/02/21, for those who scheduled their sessions on Tuesdays and Fridays.

A.2 Interaction topics and the two questions from the two discussion themes

Topic	Neutral Discussion Theme	Covid-Related Discussion Theme
Work	What do you do for a living? What do you like the most about your work situation? What do you do for a living? What are the worse aspects of your work situation?	What do you do for a living? What do you like the most about your work situation during the pandemic? What do you do for a living? What are the worse aspects of your work situation during the pandemic?
Leisure time and passions	What do you do for fun in your spare time? What role does it play in your life? Can you tell me about the things you like the most in the world, and why? For example, a favourite place, music, food, or whatever comes to mind.	In these times of the pandemic, what do you do for fun in your spare time? What role does it play in your life? Can you tell me about the things you like the most during the pandemic, and why? For example, a favourite place, music, food, or whatever comes to mind.
Finances	How do you feel about your financial situation? Where do you want to be one year from now financially?	After a year of dealing with the pandemic, how do you feel about your financial situation? Where do you want to be once the pandemic is over, financially?
Relationships	Can you tell me about your closest relationships and the important people in your life? How do these relationships are making you feel? Would you mind sharing a memory about your family or your partner? Something that you did together.	Can you tell me about your closest relationships and the important people that you spent time with during the pandemic? How do these relationships are making you feel? Would you mind sharing a memory about your family or your partner? Something that you did together during the pandemic.
Social life	Can you tell me about your social-life? How often do you socialize, and how do you feel about it? Would you mind sharing a memory about you and your friends? Something that you did together.	Can you tell me about your social-life? Since the pandemic started, how often have you been socializing, and how do you feel about it? Would you mind sharing a memory about you and your friends? Something that you did together during the pandemic.
Mental Health	How do you emotionally feel? Have you been bothered any time recently by low feelings, stress, or saadness? What do you do to take care of your mental health? What makes you feel better when you are down?	How do you emotionally feel? Have you been bothered during the pandemic by low feelings, stress, or saadness? Since the pandemic started, what were you doing to take care of your mental health? What makes you feel better when you are down?
Physical Health	How do you physically feel? How does your body affect your daily activities? What are your healthy habits, and the not so healthy habits? Would you like to change some of these habits?	How have you been feeling physically since the pandemic started? How does your body affect your daily activities? What are your healthy habits, and the not so healthy habits, during these days of the pandemic? Would you like to change some of these habits?
Personality	What do you think are your stronger qualities? And what do you think are your weaker qualities? What do you think that other people consider being your strengths and weaknesses?	During the period of the pandemic, What do you think were your stronger qualities? And what do you think are your weaker qualities? Do you think that the pandemic changed the way that other people perceive your strengths and weaknesses?
Goals and Ambitions	Would you mind sharing with me what is your most prominent goal or ambition for the near future? Can you think about a meaningful goal or ambition from your past? Did you get to accomplish this goal?	Would you mind sharing with me what is your most prominent goal or ambition for after the pandemic is over? Can you think about a meaningful goal or ambition that you had just before the pandemic? Did you get to accomplish this goal?
Routine and Daily Activities	How does your day usually looks like? What is your daily routine? How do you manage to balance your commitments while investing in yourself? Do you feel that you got it under control?	How does your day usually looks like during this period of the pandemic? What is your daily routine? Since the pandemic started, How did you manage to balance your commitments while investing in yourself? Do you feel that you got it under control?

Table A.1: Interaction topics and the two questions from the two discussion themes.

A.3 Full list of questionnaires and their order in each session

A.3.1 Session 0 - Induction Questionnaire

Participants reported on several demographic parameters, including:

- First language (i.e., "Is English your first language?").
- Age in years.
- Gender identity.
- Biological sex.
- Highest education level achieved.
- Employment status.
- Occupation sector.
- Martial status.
- Number of people living at the same house.
- Country of origin.
- Country of residence.
- Previous experience with social robots.

Then, participants filled these questionnaires in the following order:

- Distress disclosure index (DDI; Kahn & Hessling, 2001; Kahn et al., 2012).
- the short-form UCLA loneliness scale (ULS-8; Hays & DiMatteo, 1987).
- COVID-19 threat perception (CTP; Imhoff & Lamberty, 2020).
- COVID 19 worries scale (CWS; An adapted and shorter version of "COVID Stress Scales" by Taylor et al., 2020).
- COVID-19 conspiracy belief scale (CCB; Imhoff & Lamberty, 2020).
- Extraversion items of the Big Five personality scale (Saucier, 1994).

A.3.2 Sessions 1 to 10

When starting each session, participants were asked to enter their Prolific ID and their participant number. Following, participants were asked to answer the Immediate Mood Scaler (IMS-12; Nahum et al., 2017)) for reporting their mood before interacting with Pepper. After finishing their interaction with Pepper, participants went back to the Qualtrics page and answered the rest of the questionnaires in the following order:

- Agency and Experience (adapted from H. M. Gray et al., 2007).
- Comforting responses scale (adapted from R. A. Clark et al., 1998).
- Subjective self-disclosure (an adaptation of the work and studies sub-scale from Jourard's Self-Disclosure questionnaire Jourard, 1971).
- Post interaction IMS-12 (adapted from Nahum et al., 2017).

Then, participants evaluated the robot and the interaction on several scales, including:

- Interaction quality (IQ; an adapted and adjusted version by Croes and Antheunis (2020) for a scale by Berry and Hansen (2000)). Each interaction included two random items out of six, except for the mid-session (session 5) and the last session (session 10) that included all six items of the scale.
- Communication competence (an adapted and adjusted version by Croes and Antheunis (2020) for a scale by Demeure et al. (2011)).
- Disclosure quality (an adapted and adjusted version by Croes and Antheunis (2020) for a scale by Ledbetter (2009)).
- Friendliness and warmth (one item from Petty and Mirels (1981) and two items from Birnbaum et al. (2016b), as suggested by Ho et al. (2018)).

Finally, participants reported their feelings of loneliness via the ULS-8 (Hays & DiMatteo, 1987).

A.3.3 Unique Sessions

Session 3 Before completing the session participants were asked if they could answer three more additional open-ended questions. The participants were clarified that this part is optional and not obligatory. The open-ended questions were:

- What do you think about Pepper at this point of your participation?

- What are the best things about talking to Pepper?
- What are the worse things about talking to Pepper?

Session 5 - Mid-Session Participants followed the same procedure as in the other sessions, but also answered to the following additional questionnaires:

- IQ (Croes & Antheunis, 2020; Berry & Hansen, 2000). This session included all six items of the scale.
- Perceived stress (PPS; Cohen et al., 1983).
- CTP (Imhoff & Lamberty, 2020).

Session 10 - Last Session Participants followed the same procedure as in the other sessions, but also answered the following additional questionnaires:

- IQ (Croes & Antheunis, 2020; Berry & Hansen, 2000). This session included all six items of the scale.
- Participants were asked if they are going to miss Pepper (a yes or no question).
- DDI (Kahn & Hessling, 2001; Kahn et al., 2012).
- PPS (Cohen et al., 1983).
- CTP (Imhoff & Lamberty, 2020).
- CWS (Taylor et al., 2020).
- CCB (Imhoff & Lamberty, 2020).

Then, participants were asked the following open-ended questions:

- What do you think about Pepper after your participation in the study?
- What are the best things about talking to Pepper?
- What are the worse things about talking to Pepper?
- Can you please tell us about your relationship with Pepper? How did Pepper make you feel in the past month?
- Can you please share a prominent memory that you have from your interactions with Pepper?

Finally, participants reported on the following items concerning their quality of life during the COVID-19 pandemic.

- Social isolation and social participation (an adjusted version of the social participation questionnaire (Densley, Davidson, & Gunn, 2013) and the short social participation questionnaire for lockdowns (Ammar et al., 2021, 2020; Bastoni et al., 2021)).
- Life satisfaction - before and during the pandemic (an adjusted version of the the short life satisfaction questionnaire for lockdowns (Ammar et al., 2020; Bastoni et al., 2021) that was influenced from Diener, Emmons, Larsem, and Griffin (1985)).

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