Modeling of Robot Behaviors Based on Social Signals for Facilitating Engagement in Healthcare Settings

(健康医療の現場における関与促進のための
社会的信号に基づくロボットの行動モデリング)

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School of Integrative and Global Majors
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March　２０２１

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私と小鳥と鈴と

- 金子みすず

わたしが手をひろげても、
お空はちっともとべないが、
とべる小鳥はわたしのように、
地面をはやくは走れない。
わたしがからだをゆすっても、
きれいな音はでないけど、
あの鳴るすずはわたしのように
たくさんなうたは知らないよ、
すずと、小鳥と、それからわたし、
みんなちがって、みんないい。

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Abstract

This study proposed models of robot behaviors. To design robot behaviors in temporal and dynamic contexts of healthcare settings, this research investigated how to facilitate engagement based on social signals, which are combinations of behaviors to change others' behaviors or inner states in communication. There were two approaches to facilitate engagement in this study. The first approach was to apply human social signals to robot behaviors. The second approach was to recognize human social signals to create adaptive robot behaviors. Based on the two approaches, a conceptual model and a probabilistic model were proposed.

The conceptual model represents the process of creating robot behaviors when affective engagement is involved in the interaction. This model assumes that a robot's behaviors can be adaptive by recognizing and predicting a humans' engagement process and states. With this framework, we found that combinations of specific behaviors can be used for a robot to initiate engagement in healthcare settings.

The probabilistic model is for the prediction of smile-related behaviors. Particularly, smiles and prosocial behaviors were investigated in this study. This model showed the potential of recognizing human social signals. Also, this model showed the potential of predicting smile-related behaviors. It can be applied to recognize and arouse smiles with a robot and maintain engagement in therapy.

The future research will consider four directions. First, we will investigate the applicability and generalizability of the models in other situations of healthcare settings. Second, we will investigate individualized healthcare services with the models. Third, we will investigate the possible array of robot behaviors to influence humans' affect and trigger smiles. Lastly, we will investigate other smile-related behaviors which can be facilitated by robot behaviors arousing smiles.

The contribution of this study is to advance knowledge and data in social robotics and human informatics. This study provides a holistic framework for designing robot behaviors by considering changes in contexts of healthcare settings. The proposed models are expected to apply for empowering human healthcare with a social robot.

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Chapter 1

Introduction

What would you do if you encountered a social robot in a hospital? Social robots are a type of robots that can socially communicate with humans [8, 16]. With the rise of social robots, robots having human-like or animal-like appearance have been used in healthcare settings [19, 26]. The appearance of social robots can draw attention easily [8]. However, we do not know what to do with a robot [41]. For therapeutic interactions between a robot and a human in healthcare settings, a robot needs to initiate an interaction and induce participation from a user [29, 75]. Therefore, this study aims to provide a framework for designing robot behavior in dynamic healthcare settings.

Particularly, this study explored how to design robot behaviors to initiate and maintain engagement based on social signals. Initiating engagement was investigated in general situations of hospitals. Maintaining engagement was investigated in a therapeutic setting. By suggesting a framework for designing behaviors of robots to facilitate engagement, it is expected to empower human healthcare and contribute to human informatics.

1.1 Problem Statement

People do not know what to do with a social robot. Since Kismet, the first robot expressing social and emotional behaviors, was developed in 1998, the functions and appearance of social robots have been improved [17, 16]. However, social interactions between a human and a robot are still not smooth [1]. The difficulty of designing robot behaviors is from a myriad of variables in social interactions. In the long-term interaction with a robot, people do not know what to do next with

the robot. It will bring about losing interest in the robot. To create the long-term interactions and deal with the diversity of interactions, this study suggests models for adaptive robot behaviors based on social signals.

1.2 Purpose of the Research

The purpose of this research is to propose models of robot behaviors to facilitate engagement in healthcare settings. Why do robot behaviors need to be considered in healthcare settings? Previous studies showed the potential of using social robots to make up for a scarce workforce or allow medical or therapeutic professionals to focus on more advanced treatments [22, 26, 59, 2]. To create positive interactions between a robot and a human in healthcare processes, robots' behaviors need to be designed in temporal and dynamic contexts [16]. Then, why does engagement in interactions with a robot need to be facilitated in healthcare settings? Engagement is a state with high interest, attention, or focus [44]. Initiating and maintaining engagement is necessary to induce participation in an activity with a robot and maximize healthcare effects [102]. If engagement in interactions with a robot is important to improve the quality of healthcare, how can we facilitate it? Based on these questions, this research was conducted to suggest a framework of designing robot behaviors to facilitate engagement in healthcare settings.

To facilitate engagement, this study applied social signals in the context of an interaction process. Social signals are combinations of behaviors to convey intentions and change others' behaviors [95, 142]. To design robot behaviors based on social signals, two approaches were adopted. The first approach is to investigate whether social signals in human-human interactions can be applied to robots. We considered possible social signals to design robot behaviors. This approach was applied to initiate engagement in general situations of a hospital. The second approach is to investigate the recognition of human social signals to create adaptive robot behaviors. Particularly, the detection of human smiles and prediction of smile-related behaviors were explored. This approach was applied to specific therapy for children with Autism Spectrum Disorders (ASD). With the two approaches, the proposed models in this study consist of the temporal and dynamic context based on social signals when designing robot behaviors.

The value of this study is that it provides a framework considering changes in contexts for designing robot behaviors. Existing models for engagement in human-robot interaction focused on specific systems of a robot, such as automatic

recognition or prediction of engagement [64, 65, 118, 117]. Different from the models, this study was conducted to provide models with a holistic approach. By suggesting a conceptual model, this study covers both the initiation and maintenance of engagement. Initiation of engagement was explored in general situations, while maintenance of engagement was explored in a specific situation. Furthermore, this study proposes a computational model to create adaptivity of robot behaviors. To recognize a type of engagement, video recording and electromyogram were applied. Based on the recognition, prediction of the next engagement was performed with a Bayesian approach. The two models are expected to apply for empowering human healthcare with a social robot. Academically, the contribution of this study is to advance knowledge and data in social robotics and human informatics.

1.3 Research Questions and Thesis Outline

The goal of this study is addressed by exploring two main research questions (RQ) and hypotheses (H) as follows:

- **RQ 1.** What kinds of behavioral planning of a robot are used to initiate engagement in healthcare settings?
- **H 1-1.** Combinations of human behaviors can be used as behavioral planning of a robot to initiate engagement in healthcare settings.
- **H 1-2.** Depending on situations, different behavioral planning of a robot will be preferred in healthcare settings.
- **RQ 2.** What kinds of behavioral factors affect the occurrence of prosocial behaviors toward a robot in robot-assisted therapy?
- **H 2-1.** There will be a positive relationship between human smiles and prosocial behaviors toward a robot in robot-assisted therapy.
- **H 2-2.** After a robot's movement, a series of behaviors of each child will be observed in robot-assisted therapy.
- **H 2-3.** The series of behaviors will be represented by conditional probability in robot-assisted therapy.
- **H 2-4.** The series of behaviors will predict the occurrence of prosocial behaviors toward a robot in robot-assisted therapy.

To investigate the research questions, multiple perspectives were used. RQ 1 is to explore how to initiate engagement by applying appropriate human social signals to robots in a hospital. This question was investigated with a design perspective and a survey-based experiment (see Chapter 3). RQ 2 is to explore how to maintain engagement by recognizing social signals and predicting the next engagement of a human in robot-assisted therapy. This question was investigated with psychological and computing perspectives using video analysis and statistical modeling (see Chapter 4 and Chapter 5).

This dissertation includes seven chapters. Chapter 1 addresses the outline of this research. Chapter 2 introduces the research background and conceptual framework. Based on the literature review, potentially significant variables were arranged to create models of designing robot behaviors. Chapter 3, 4, and 5 are to explore RQ 1 and 2 by developing a conceptual model and a computational model. The research discussion and limitation are addressed in Chapter 6, and finally, the conclusion of this research and future directions are addressed in Chapter 7.

Chapter 2

Literature Review

This chapter introduces the conceptual and methodological background for this study. The purpose of this study is to create models of robot behaviors based on social signals to facilitate engagement in healthcare settings. This chapter explains why the research purpose and concepts were selected and how to achieve the goal based on a literature review on engagement, social signals, and models of robot behaviors in the academic field of psychology and Human-Robot Interaction (HRI). Three sections are included in this chapter. The first section describes what engagement means in HRI and what limitations were found in maintaining engagement. The second section is to review what social signals are and how to apply them to robot behaviors. The aspects of applying social signals are divided into two purposes; expression of robot behaviors and detecting social signals of humans. The final section is to review models for engagement in HRI and the limitations of existing models. The section also describes what kinds of variables can be considered for designing robot behaviors in healthcare settings. The possible variables will be investigated to create a conceptual model and a computational model in this study.

2.1 Engagement in Human-Robot Interaction

Engagement has been investigated as an important research topic in HRI [5, 102]. HRI is a field of study to understand, design, develop, or evaluate robotic systems which can interact with humans [10, 45]. To create long-term interaction and to achieve goals between humans and robots, maintaining engagement has been considered [2, 65, 118, 135]. Particularly, the expression of engaging robot behaviors and recognition of engagement from humans were two main perspectives to create

adaptive robot behaviors [1, 102]. Also, designing robot behaviors based on a user's engagement has been suggested as an essential element to create social robots [130, 133]. Therefore, this section covers the definition and measurement of engagement.

2.1.1 Defining Engagement

Engagement occurs during an interaction, and it involves interest, attention, or focus [44]. Engagement has been investigated with various definitions and perspectives in HRI [102, 129]. This section introduces two types of classification for defining engagement.

One is the perspective which defines engagement as a process or a state. As a process, engagement goes through steps in an interaction [129]. For example, at least two interactors start, maintain, and end their engagement during an interaction. Also, there can be more phases in engagement. In addition to starting, maintaining, and ending, four more steps, which are joining, abandoning, suspending, and resuming, were suggested [13]. On the other hand, engagement can be defined as a state. This viewpoint focuses on binary states, which are engaged or unengaged [61]. For example, the number of occurrences of gazing or laughing can indicate the engaged states.

Engagement can be also classified with the target of engagement. When the target of engagement is a task, it can be defined as task engagement [23]. In this engagement, users focus on performing the task, not interacting with a robot. The role of a robot is to assist the task. On the other hand, when the target of engagement is a human, robot, or agent, it can be defined as social engagement [97]. In social engagement, social activities or social behaviors are involved between a robot and a human. However, it has been increased to apply robots to dynamic environments. Therefore, both task and social engagement can be involved in HRI. For instance, a robot asked a human to teach the robot to differentiate objects in a study. Each human participant engaged in the robot to perform the collaborative learning task [63]. In this case, either social or task engagement can be focused depending on the research purpose.

The purpose of this research is to design robot behaviors to facilitate engagement in general healthcare settings and specific robot-assisted therapy. When considering that healthcare settings require various types of engagement depending on time and purposes, we adopted both process and state viewpoints. Process viewpoint was applied to a conceptual model, while state viewpoint was applied to a computational

model. In this research, engagement was defined as the process including the start, maintenance, and end of perceived behaviors. Also, engagement was defined as the state of perceived behaviors, which are an indicator of engagement. Regarding the target of engagement, this research focused on social engagement. In particular, the potential of applying social signals to robot behaviors and to recognize human behaviors based on social signals were investigated between a robot and a human.

2.1.2 Measuring Engagement

To measure engagement, various types of the index have been investigated in HRI. Particularly, social engagement has been measured by verbal or nonverbal behaviors. Verbal behaviors included initial vocalizations and verbal responses. Verbal behaviors were measured by how many or much a participant mentions targeted verbal words or sentences [2, 148]. Nonverbal behaviors were focused on eye gazing, smiling, and gestures [65, 78, 117, 130, 135]. Gaze is a behavior of looking with intention and it is considered as a signal of attention [38, 2]. Smile is one of the facial expressions, which provide affective and social information [92, 112]. Smile is considered not only as an indicator of positive affect but also as social signals [87]. Gesture includes body movements, such as waving, head shaking, nodding, bowing [103, 113]. These nonverbal behaviors can be analyzed by stability or variance, which are based on the perspective of static engagement. Also, these behaviors can be analyzed by frequency and duration of occurrence, which are based on dynamic analysis considering time [5].

There are various types of methods to measure engagement. A commonly used method was a questionnaire [30, 91]. Also, measuring affective and behavioral engagement has been tried with noninvasive and external devices; video cameras for tracking facial and body movements, eye trackers for tracking eye gaze, and EMG sensors for tracking facial muscle contraction [5, 63, 76]. These methods were combined with machine learning classifications for automatic pattern recognition [48, 91, 118, 136]. In particular, EMG data can provide information for analysis of smiles [34, 48]. When facial expressions are not observable, EMG signals can be used to recognize smiles. Also, it has advantages compared to other sensing methods, such as using screen-based eye trackers and electroencephalography [42, 33]. EMG sensors with surface electrodes are easier to attach to human skins than EEG sensors. EMG signals can be recorded in healthcare settings as well as in laboratory environments [43, 121]. Therefore, each method can provide different aspects of engagement, and combining several methods might complement the measurement of engagement.

In this research, social engagement was measured by questionnaire, video analysis, and EMG signal processing. First, a questionnaire was used to explore users' evaluations on a robot's behaviors when initiating engagement. Next, affective and behavioral engagement were focused in robot-assisted therapy. Particularly, smiles were analyzed as an indicator of affective engagement. To measure durations of smiles, videos and EMG signals were recorded from each participant of the therapy.

2.2 Designing Robot Behaviors

The start of engagement might be possible by designing human-like behaviors. As humans tend to understand and predict the behavior of animals, plants, and objects by anthropomorphizing them, people might easily engage in a robot which shows human-like behaviors [14, 25]. Another way of designing robot behaviors to maintain engagement is based on the recognition of human behaviors [2]. Regarding designing a social robot, Fong, Nourbakhsh, and Dautenhahn suggested four design elements [39]. The first design element is to design a robot to perceive human behavior and interpret social cues. The second element is to design a robot that behaves and talks according to social customs and norms. The third element is to design a robot that expresses thoughts or emotions through social cues such as facial expressions, movements, and voice. The fourth design element is to make a robot that pays attention and acts immediately for real-time communication with a human. This research focuses on the first and fourth design elements, which are related to recognizing human behaviors and expressing social behaviors timely.

2.2.1 Social Signals

In human interactions, social signals are combinations of behaviors to change others' behaviors or inner states in communication [95, 142]. Communication is to give and take informational or emotional messages [115]. Therefore, a sender of the signal conveys communicative information to influence others. A recipient of the signal tries to decode the purpose of the behaviors. The intention of social signals can be various, as human communications are multipurpose in our daily lives [95]. Humans interact with other humans to build relationships, play a social role, or help each other. To convey the intention, using appropriate nonverbal as well as verbal behaviors is essential for human interaction. Nonverbal behaviors are

generally improvised, unconscious, and subtle. Verbal behaviors are more direct and controllable than nonverbal behaviors [4]. Therefore, it is necessary for smooth communication to send signals to others and decode signals from others.

What if we apply human social signals to the design and operation of robots? Is it possible for humanoid social robots to send social signals in the same way as humans? Is it possible to give sociality to the robots? Although there can be many questions when applying human social signals to robot behaviors, research on social signals for creating robot behaviors has been focused in limited situations, such as greetings and approach [38, 52, 58, 70]. To signal the intention of greetings or approach, appropriate social cues were considered. Social cues are biologically and physically prominent features [38, 141]. The combinations of social cues were applied to create a social signal. Then, how can we maintain engagement in changing contexts after greetings or approach? Designing robot behaviors based on social signals were not fully investigated. Particularly, research on applying social signals for maintaining engagement is needed to design robot behaviors with a long-term perspective.

Another direction of research on social signals is social signal processing of humans [108, 142]. Social signal processing was suggested to analyze social behaviors not only in human-human interactions but also in human-agent interactions [104, 141]. The purpose of social signal processing is to give social intelligence to computers or artificial agents. Research on social signal processing has focused on automatic analysis of human nonverbal behaviors to detect social signals [104, 108, 143, 140]. The main research topic was what combination of behavioral cues can be signals of psychological or social phenomena, such as empathy or interest. However, designing robot behaviors with social signal processing has not been focused on. Also, conveying social signals and maintaining engagement has not been highlighted, although human-like behavioral cues have been considered for designing robot behaviors [116, 150]. As social robots are expected to be able to act autonomously [15], designing robot behaviors based on social signals might be an essential element to create an autonomous and adaptive social robot. By applying social signals to a robot and analyzing social signals from a human, personalized robot behaviors might be created for each user.

Considering the limitations of previous research, this study focuses on designing robot behaviors based on social signals. First, the applicability of human social signals will be explored. Next, designing robot behaviors based on recognition of social signals will be explored in a long-term interaction process.

2.2.2 Verbal and Nonverbal Communication

Communication methods can be classified as verbal and nonverbal [88, 94]. Although the two methods are mostly used simultaneously in human-human interactions [94], we need to consider them separately to design robot behaviors [90].

Verbal communication includes interactions with oral methods [94]. For example, humans express interest or boredom to others in daily conversations [37]. A conversation is a process in which at least two people are exchanging words [98]. A conversation begins when at least two people express interest, while a conversation ends when at least one person expresses boredom. Although there is a myriad of ways and content of conversations, certain expressions are used when initiating a conversation [125]. At the start of a conversation, it is assumed that both parties will engage in the conversation. Thus, someone who wants a conversation tries to anticipate the possibility of engagement from another person before speaking or acting. The most frequently used types of verbal expression include calling someone's name, asking for information, providing information, and sharing on a topic. They are mostly used when initiating a conversation [124]. Another example is greetings. When starting or ending greetings, humans use direct words with relevant behaviors, such as facial expressions, gestures, and distance adjustments [74].

Nonverbal communication includes interactions with facial expressions, body movements, gestures, or postures [74]. Nonverbal behaviors have been considered as an important medium of communication [103]. In particular, it is important for smooth communication to send behavioral signals to others and to understand signals of other [88]. Nonverbal behaviors, such as smiling, eye gaze, posture, and physical contact, can be recognized as a social signal [74, 142]. The meanings of social signals from nonverbal behaviors can be interpreted differently depending on various factors, such as context, culture, relationship, and combination of other behaviors [74, 141]. As there are many factors which can be involved to decode nonverbal social signals, recognition and expression of multimodal behaviors have been focused in social robotics [1, 61, 117, 108, 145]. Therefore, acquiring multimodal databases and integrating the data have been the main agenda to decode social signals. To deal with the multimodal data, neural network algorithms were commonly used [65, 117]. However, modeling multimodal behaviors requires huge data, and it can slow a behavioral decision making of a robot.

This research approached social signals to design robot behaviors in healthcare settings. We first explored applicable human behaviors to send social signals from

Table 2.1 Verbal and nonverbal behaviors in each interaction unit.

Interaction unit	Verbal behavior	Nonverbal behavior
Beginning	Asking questions Adding conversation	Smiling Establishing eye contact Moving closer Clearing one's throat
Continuation	Making long utterances Asking personal questions Agreeing with other	Smiling Nodding Laughing Touching
Termination	Making short utterances Giving closed-ended responses Terminating conversation	Smiling Looking away Turning away Moving away

a robot. Next, we explored recognizable human social signals in robot-assisted therapy. Lastly, we explored how to design robot behaviors based on the recognition of human social signals. If we can find significant behavioral factors which can be a social signal in various situations of healthcare settings, we can detect the social signals with a small number of sensors, and we can create adaptive robot behaviors with simpler algorithms. Therefore, we summarized recognizable human behaviors in an interaction process [37, 68, 74]. These behaviors might be applied to design robot behaviors [52, 70].

Table 2.1 shows verbal and nonverbal behaviors for each interaction unit. By considering that social interaction generally proceeds in the order of beginning, continuation, and termination [3, 37, 74], an interaction process can be divided into three units. Each interaction unit includes different verbal and nonverbal behaviors. For instance, smiling is one of the nonverbal behaviors to begin an interaction. Establishing eye contact and moving closer can occur at the beginning of the interaction with smiling. Also, verbal behaviors, such as asking a question to someone, are used to start an interaction. In the middle of the interaction, behaviors showing interests, such as nodding, laughing, making long utterances, and asking personal questions, can continue the interaction. To end the interaction, humans may express less interest by showing specific behaviors, such as looking away and making short utterances. The combinations of behaviors can be referred to detect social signals from humans. Moreover, it might be possible to design robot behaviors in healthcare settings by applying combinations of human behaviors in each interaction unit.

2.3 Models of Robot Behaviors

Models have been proposed to design or control robot behaviors [101, 130]. Developing models has advantages to create HRI. As models can provide a framework to design interactions between a robot and a human, robot behaviors can be decided automatically or efficiently with a model. Also, models including perceptive and predictive systems can be used for designing adaptive robot behaviors [1]. Models for adaptive robot behaviors have considered what to perceive from human behaviors, or how to predict human behaviors [50, 81, 60]. It is essential to make a robot's behaviors flexible in order to maintain engagement and create long-term interactions in HRI [64, 117]. As this research focuses on modeling robot behaviors to facilitate social engagement, proposed models include perceiving and predicting human behaviors related to social engagement. Thus, this section covers existing models to perceive or predict human engagement for deciding robot behaviors. Based on the literature review, this section proposes a conceptual framework for developing models in healthcare settings.

2.3.1 Models for Engagement

Computational models have been suggested to recognize or predict engagement automatically. Research on developing computational models for engagement was focused on finding better algorithms. Jain et al. proposed two models to detect generalized and individualized engagement states automatically in the long-term [64]. Seven children with ASD participated in math games on a tablet for one month at home. A robot, called Kiwi, provided personalized feedback for each participant. In the study, the researchers collected data from video recordings, and engagement was measured by video, audio, and game performance features, which were extracted from videos. Video features included eye gaze, head position, and facial expression. They compared different types of computational models, such as decision trees, neural networks, support vector machines, and k-nearest neighbors with different modalities. The results showed that tree-based models with visual features were the most suitable in the setting. Javed, Lee, and Park suggested a personalized computational model for an automatic measure of engagement [65]. Five children with ASD and thirteen TD children participated in a sensory maze game. It included activities to answer questions from robots, follow instructions of robots, and help the robots build a maze. In the study, the researchers collected multimodal data from video recordings. Particularly, eye gaze, smile, vocalization, and imitation were

extracted from videos to investigate changes in engagement. They applied various machine learning algorithms, such as convolutional neural networks, support vector classification, decision trees, random forest, and k-nearest neighbors. The results showed that deep learning convolutional neural networks achieved the highest performance. Rudovic et al. proposed a personalized computational model to predict human engagement automatically [117]. Thirty-five children with autism spectrum conditions participated in therapeutic activities with an NAO robot. In the study, the researchers recorded videos to estimate engagement based on facial expressions, body movement, and vocalization. Also, they used physiological sensors to measure heart rate, electrodermal activity, and body temperature. They developed a new deep learning approach to estimate engagement, and its performance was better than traditional algorithms.

Another type of model which has been suggested for engagement in HRI is the conceptual models. This model represents a comprehensive system of a robot. Leite et al. proposed a conceptual model including affect detection and engagement to create empathic robots [80]. It was suggested to decide a robot's empathic behaviors for long-term interaction with a child. Sixteen elementary school children participated in a chess game with a robot, called iCat. The robot provided supportive behaviors, such as advice and compliment, while playing a chess game with each participant. The researchers collected data from interviews, questionnaires, and video recordings. Engagement states of participants were measured by facial cues and head direction. The results show that the robot adopting the model was perceived as empathic. On the other hand, Salam and Chetouani [120] suggested a conceptual model of engagement in a broad context. They classified the context of HRI into seven categories based on literature in HRI; competitive, informative, educative, collaborative, negotiable, social, and guide-and-follow. Each context included different types of mental states, which can be related to engagement.

For designing a robot's behaviors, it is necessary to consider both computational and conceptual models [146]. As a robot's behaviors can be adaptive based on recognition and prediction of human behaviors, a computational approach is needed. However, existing computational models focused on automatic recognition and prediction of engagement from multimodal data. For modeling, the comparison of algorithms was highlighted. Although the models provide efficient algorithms which can recognize or predict engagement, various types of input data are required with these models. Furthermore, the models were not developed to design robot behaviors. Therefore, this study explored what to recognize for engaging in specific

behaviors and how to computationally predict the engagement to design robot behaviors in robot-assisted therapy.

Also, a conceptual model is necessary to apply a robot not only to specific scenarios but also to general healthcare settings. However, existing conceptual models were too broad or too specific. Although contexts are included in the models, an interaction process was not considered, which can explain dynamic changes of interactions. Thus, this study considered an interaction process and engagement steps in a conceptual model.

2.3.2 Conceptual Framework

The purpose of this study is to propose models for designing robot behaviors based on social signals. A process of designing a robot's behaviors is described with the models to facilitate social engagement in healthcare settings. To develop models, we considered both a conceptual model and a computational model. The conceptual model represents an interaction process related to mood and emotion in healthcare settings. The computation model describes a part of the conceptual model regarding the prediction of engagement in a specific behavior.

Figure 2.1 shows the conceptual framework for creating models. This framework represents the initiation and continuation step of an interaction. In the initiation step, a robot's behaviors are investigated in joining two people's conversation and measuring temperature situation, which was selected considering the wide-ranging application of a robot in healthcare settings. We explore the possible array of combinations of verbal and nonverbal behaviors to apply social signals to a robot. In the continuation step, recognizable social signals to engage in prosocial behaviors are investigated in robot-assisted therapy for children with ASD. We explore the potential of personalized robot-assisted therapy based on the prediction of engagement.

The description of each component in the conceptual framework is as follows.

Robot behavior. Robot behaviors were adopted from human behaviors. The behaviors were selected considering a robot's functions and appearance. Therefore, different robot behaviors were applied to two different robots.

Human mood. Mood is one of affectives states [36]. While emotion is triggered by a specific event, mood is caused by internal changes or general situations. It lasts longer than emotions. As it is not clearly expressed, it is difficult to recognize mood [35].

Human appraisal. This conceptual framework is based on the appraisal theory of emotion. Different from other theories of emotions that focus on the order of

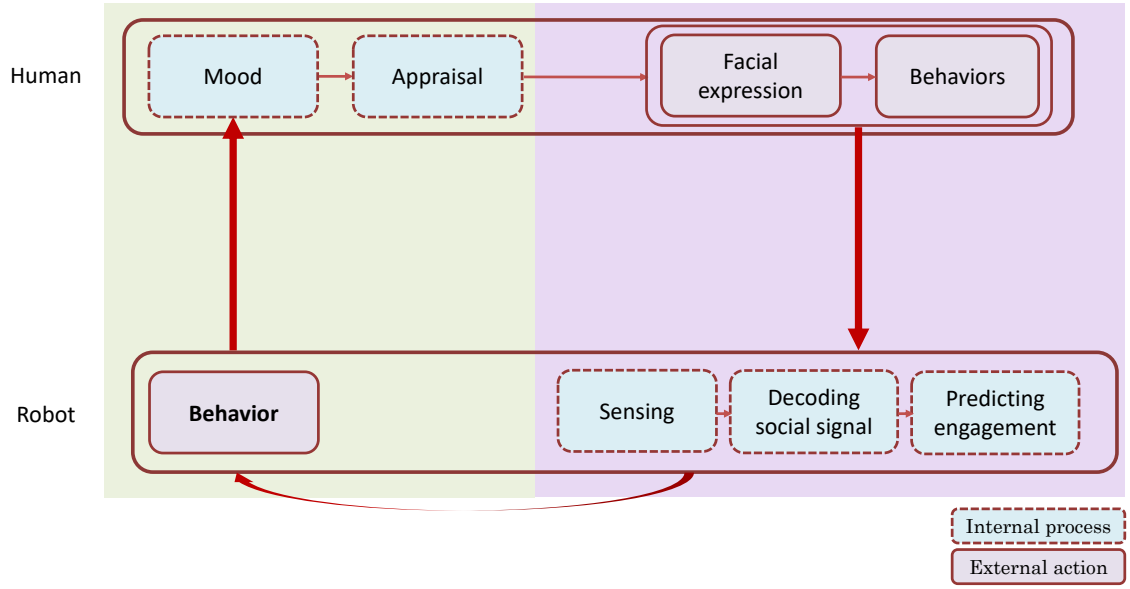

Figure 2.1 Conceptual framework in this study.

physiological arousal and emotional responses, appraisal theory focuses on one's subjective evaluations of an event. The evaluation can be expressed by a specific reaction and it can be considered in communication [89, 86, 96, 126].

Human facial expression. Human facial expression gives information to measure emotions and engagement [35, 74, 94]. Particularly, this model focused on smiles. Smiles can be an indicator of positive mood [42]. Also, smiles occur with other behaviors to send various social signals [87]. Moreover, it has been reported that smiles can be related to prosocial behaviors [49, 144].

Human behavior. Human facial expression can be related to other behaviors. In the continuation step of interaction, we focused on engaging in prosocial behaviors before, during, and after smiling in robot-assisted therapy for children with ASD. Prosocial behaviors are actions for benefiting others, such as helping [147], cooperating [18], sharing resources [32], or providing emotional support [132].

Sensing. Behaviors and physiological data can be collected by sensing technology. In this study, smiles and prosocial behaviors were recognized by video analysis. Also, EMG sensors were adopted to detect facial muscle activities related to smiles.

Decoding social signals. We assumed that human smiles and concurrent or subsequent behaviors can be social signals to indicate engagement in prosocial behaviors. Therefore, this study investigated a series of behaviors after detecting smiling in robot-assisted therapy.

Predicting engagement. This model is targeted to predict engagement in smile-related behaviors. In this study, the prediction of engagement in prosocial behavior was performed based on the Bayesian theorem with a computational model. This approach can be used when we know possible variables related to engagement in smile-related behaviors. Also, a Bayesian approach can deal with uncertainty and subjectivity in the posterior probabilities of smiles [7, 53, 57, 77].

With the conceptual framework, we assume that first, various internal or environmental factors can influence the mood of a person. The person might be a visitor, a patient, or a medical practitioner in healthcare settings. A robot's behavior might be a factor to influence the mood, and then the person's appraisal can be changed depending on the perception of the robot. Second, a facial expression might be changed depending on the appraisal. Particularly, smiling can be involved in therapeutic activities with a robot. When a therapeutic purpose is to facilitate smile-related behaviors, we may sense and decode social signals including smiling to predict the next engagement in the behavior. Based on the recognition and prediction of engagement, this model can guide the next behaviors of a robot.

There are possible advantages of smile analysis in robot-assisted therapy. First, smiling is an innate and recognizable behavior [105, 112, 128]. The first smiles using mouth corners can be involuntarily seen during the neonatal period. In the fourth week following birth, infants can smile actively by moving muscles around their lips and eyes [92, 128]. Although children with ASD have difficulty recognizing the smiles of others, they can express voluntary smiles with those muscles [54, 123]. Moreover, smiles can provide various social and emotional information [112]. The meanings of smiles can be different depending on other behaviors [112]. Also, the interpretation of other behaviors before, during, or after smiles can vary [93]. For instance, smiling when talking about positive things can be explained differently from smiling when talking about negative things [131]. Smiles could be a various social signal with other behaviors [87]. Thus, if a robot can sense smiles from a child and predict engagement in smile-related behaviors with the proposed models, it might be possible to create robot behaviors to facilitate the next engagement.

Chapter 3

Initiating Engagement

The purpose of this chapter is to explore possible robot behaviors to initiate engagement. We investigated combinations of robot behaviors to facilitate engagement at the beginning of the interaction in healthcare settings. First, we explored human behaviors to apply them to a robot. In particular, two different situations of a hospital were selected. One was for a robot to join a conversation of two hospital visitors. In this situation, four types of behavioral planning were investigated. The behaviors were selected from conversation-starting strategies of human interactions [122, 124]. Another situation was for a robot to measure the temperature of a patient. In this situation, two types of measuring temperature were investigated, which were direct touch by a robot and indirect touch by a robot with a thermometer. We explored whether we can apply the combinations of human behaviors to a robot in healthcare settings. Also, we explored which combination of robot behaviors is more preferred as behavioral planning of a robot to initiate engagement. Therefore, the research question and hypothesis are as follows.

RQ 1. What kinds of behavioral planning of a robot are used to initiate engagement in healthcare settings?

H 1-1. Combinations of human behaviors can be used as behavioral planning of a robot to initiate engagement in healthcare settings.

H 1-2. Depending on situations, different behavioral planning of a robot will be preferred in healthcare settings.

To answer the research question and to verify the hypothesis, we conducted survey-based experiments with psychological measurements to evaluate a robot's behaviors [12]. If the hypothesis is supported, it indicates that we could propose a way of designing robot behaviors. Based on the results of human evaluation, first, we can prioritize a robot's behaviors in specific social situations. More preferred

robot behaviors by human evaluators can be perceived as more suitable to initiate engagement, which increases the possibility of engagement. Therefore, highly evaluated behaviors might be better for the first robot behavior in an interaction with a human. Second, we can create HRI scenarios by combining possible human responses on a robot's behavioral planning.

3.1 Methods

Two experiments were conducted to investigate what kinds of behavioral planning can be used for a robot to initiate engagement in healthcare settings. The first experiment was designed to explore combinations of robot behaviors to join two people's conversations. Four behavioral plannings were selected as independent variables, which include asking a question, adding to the conversation, looking alternatively at others, and throat clearing. They were selected based on conversation-starting strategies of humans, frequency of use, and ease of implementation [37, 122, 124]. The dependent variables were sociability, a core feature of a social robot; intelligence and politeness, which are required for smoothly joining in a conversation between two people; and likability, which can be related to the first impression of the robot.

The second experiment was designed to explore combinations of robot behaviors to measure temperature. Two behavioral plannings were selected as independent variables, which include direct touch by a robot hand and indirect touch by a thermometer with a robot. They were applied to a robot considering the effects of interpersonal distances and touching behavior [72, 73, 127]. The dependent variables were empathy, sociability, safety, and knowledgeability of the robot.

3.1.1 Participants

Twenty-four adults (10 males and 14 females) participated in the experiments. The average age of participants was 30 years old (23–35 years, SD = 3.61). They were recruited randomly by using an online survey website. They received a $ 10 gift certificate as a reward for participation. All subjects were familiar with digital devices, such as computers, smartphones, and tablet PCs; however, they had no experience interacting with a robot.

Figure 3.1 LEGO Boost Creative Toolbox used for video clips and images.

3.1.2 Stimuli

A robot was created with the LEGO Boost Creative Toolbox (Figure 3.1), and the robot was used in video clips and scenario images. The stimuli in the first experiment were four video clips and scenario images. All the video clips showed that the robot is looking at two people and approaching them in common. Then, each clip showed one of four behavioral plannings for the robot to join their conversation; asking a question ("How can I help you?"), adding to the conversation ("Go up to the second floor to get to the Department of Internal Medicine."), looking alternatively at others (eye contacting two visitors one by one without words), and clearing its throat. The voice of the robot was created with a text-to-speech program. Also, scenario images were used to help the understanding of the four types of behavioral plannings (Figure 3.2).

The stimuli in the second experiment were two video clips. All the video clips showed verbal and nonverbal greetings including eye contacting and approaching. Then, each clip showed one of two behavioral plannings for the robot to measure

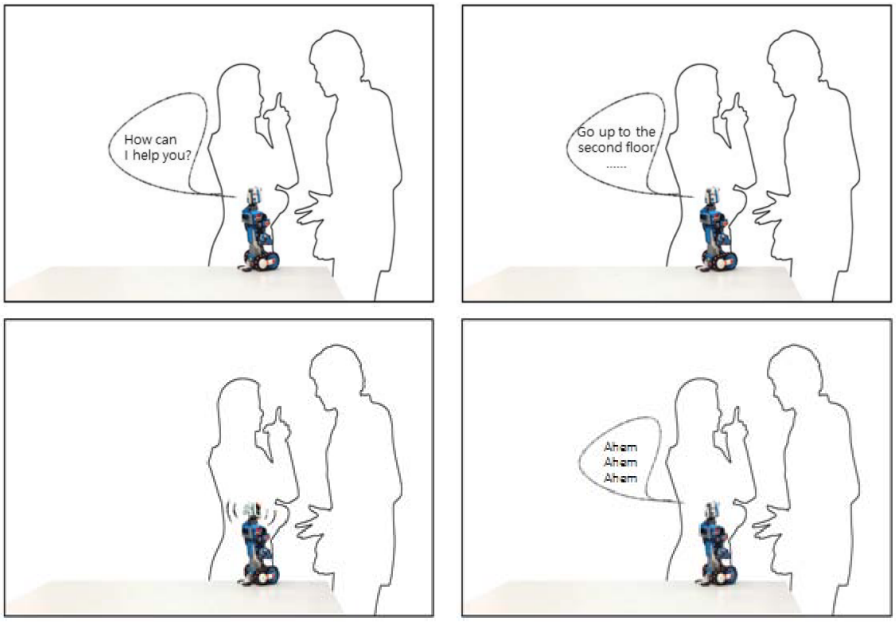

Figure 3.2 Four behavioral plannings of a robot to join two people's conversation.

temperature; measuring temperature by touching a patient's forehead with its hand and measuring temperature using a thermometer.

3.1.3 Procedure

All participants were informed about the experiments. They voluntarily participated in the two experiments. All participants watched a total of six video clips (four video clips for the first experiment and two video clips for the second experiment) in random order, and then answered questionnaires about the robot's behavioral plannings to initiate engagement.

3.1.4 Measurement

Four measurement scales were used as dependent variables for the first experiment. To evaluate the robot's behavioral plannings to join two people's conversations, we investigated the sociability, intelligence, politeness, and likability of the robot. All items of the measurements were scored on a seven-point Likert scale.

The five items of sociability were adopted considering the high reliability based on factor analysis in previous study [110]: "Looked gloomy/Looked cheerful," "Looked unfriendly / Looked friendly," "Looked negative / Looked positive," "Looked cold /

Looked warm," and "Looked bad / Looked good." These items showed high internal consistency of sociability in this study (Cronbach's $\alpha = 0.96$).

The five items of intelligence were adopted considering the sufficient reliability based on factor analysis in previous study [11]: "Looked incompetent / Looked competent," "Looked ignorant / Looked knowledgeable," "Looked irresponsible / Looked responsible," and "Looked unintelligent / Looked intelligent," and "Looked foolish / Looked sensible." These items showed high internal consistency of intelligence in this study (Cronbach's $\alpha = 0.97$).

The seven items of politeness were adopted considering the high reliability based on factor analysis in previous study [79]: "Was irresponsible / Was responsible," "Was unprofessional / Was professional," "Was unhelpful / Was helpful," "Was insincere / Was sincere," "Was inconsiderate / Was considerate," "Was impolite / Was polite," and "Was unfriendly / Was friendly." These items showed high internal consistency of politeness in this study (Cronbach's $\alpha = 0.98$).

The five items of likability were adopted considering the sufficient reliability based on factor analysis in previous study [11]: "Dislike / Like," "Unfriendly / Friendly," "Unkind / Kind," and "Awful / Nice." These items showed high internal consistency of likability in this study (Cronbach's $\alpha = 0.97$).

Four measurement scales were used as dependent variables for the second experiment. To evaluate the robot's behavioral plannings to measure temperature, we investigated the empathy, sociability, safety, and knowledgeability of the robot. All items of the measurements were scored on a seven-point Likert scale.

The ten items of empathy were adopted from a previous study [84]: "Making you feel at ease," "Letting you tell your story," "Really listening," "Being interested in you," "Fully understanding your concerns," "Showing care and compassion," "Being positive," "Explaining things clearly," "Helping you take control," and "Making a plan of action with you." These items showed high internal consistency of empathy in this study (Cronbach's $\alpha = 0.93$).

The eleven items of sociability were adopted from a previous study [110]: "Looked cheerful," "Looked friendly," "Looked warm," "Looked happy," "Looked likable," "Looked sympathetic," "Looked compassionate," "Looked gentle," "Looked tender," "Looked emotional," "Looked attractive." These items showed high internal consistency of sociability in this study (Cronbach's $\alpha = 0.97$).

The two items of safety were adopted from a previous study [11]: "Anxious / Relaxed," and "Quiescent / Surprised." These items showed a reliable internal consistency of safety in this study (Cronbach's $\alpha = 0.84$).

The eight items of knowledgeability were adopted from previous study [110]: "Looked competent," "Looked knowledgeable," "Looked intelligent," "Looked exert," "Looked reliable," "Looked useful," "Looked trustworthy," "Looked likable." These items showed high internal consistency of knowledgeability in this study (Cronbach's $\alpha = 0.94$).

3.2 Results

The results show which behavioral plannings were highly evaluated by the participants. The behavioral plannings were selected to initiate engagement in two different situations of the healthcare setting, which are joining a conversation and measuring temperature.

3.2.1 Joining a Conversation

The assessment of the robot's sociability varied according to combinations of robot behaviors ($F(3, 69) = 24.48$, $p < .005$). The participants assessed the robot's sociability as higher when the planning included adding to conversation ($M = 5.13$, $SD = 1.05$) and asking a question ($M = 5.08$, $SD = 1.09$) than looking alternatively at others ($M = 3.44$, $SD = 1.14$) and throat clearing ($M = 3.49$, $SD = 1.57$) (Figure 3.3).

The assessment of the robot's intelligence varied according to combinations of robot behaviors ($F(3, 69) = 61.06$, $p < .005$). The participants assessed the robot's intelligence as higher when the planning included adding to conversation ($M = 5.73$, $SD = 1.11$) and asking a question ($M = 5.32$, $SD = 1.15$) than looking alternatively at others ($M = 2.32$, $SD = 1.04$) and throat clearing ($M = 3.5$, $SD = 1.50$) (Figure 3.4).

The assessment of the robot's politeness varied according to combinations of robot behaviors ($F(3, 69) = 49.74$, $p < .005$). The participants assessed the robot's politeness as higher when the planning included adding to conversation ($M = 5.66$, $SD = 1.08$) and asking a question ($M = 5.35$, $SD = 1.13$) than looking alternatively at others ($M = 2.82$, $SD = 1.02$) and throat clearing ($M = 3.29$, $SD = 1.55$) (Figure 3.5).

The assessment of the robot's likability varied according to combinations of robot behaviors ($F(3, 69) = 25.23$, $p < .005$). The participants assessed the robot's likability as higher when the planning included adding to conversation ($M = 5.21$, $SD = 1.03$) and asking a question ($M = 5.07$, $SD = .90$) than looking alternatively at others ($M = 3.07$, $SD = 1.04$) and throat clearing ($M = 3.38$, $SD = 1.71$) (Figure 3.6)

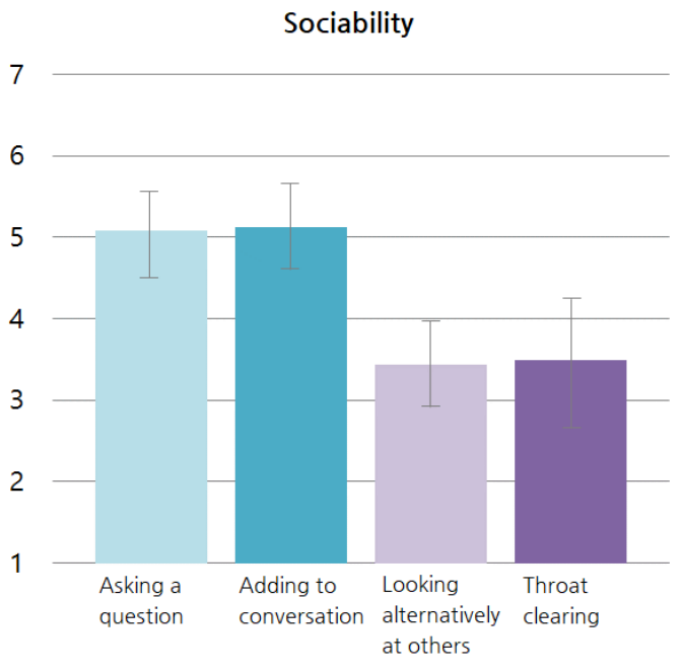

Figure 3.3 Perceived sociability depending on combinations of robot behaviors. The error bar means standard error.

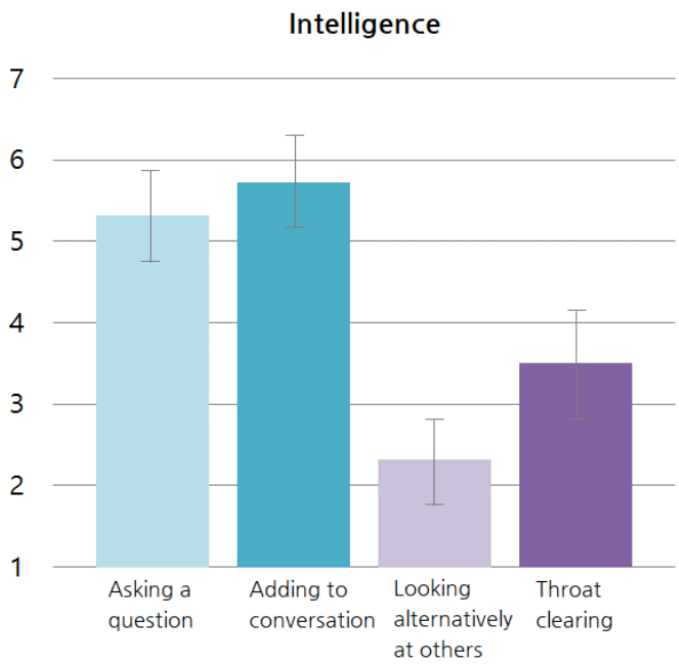

Figure 3.4 Perceived intelligence depending on combinations of robot behaviors. The error bar means standard error.

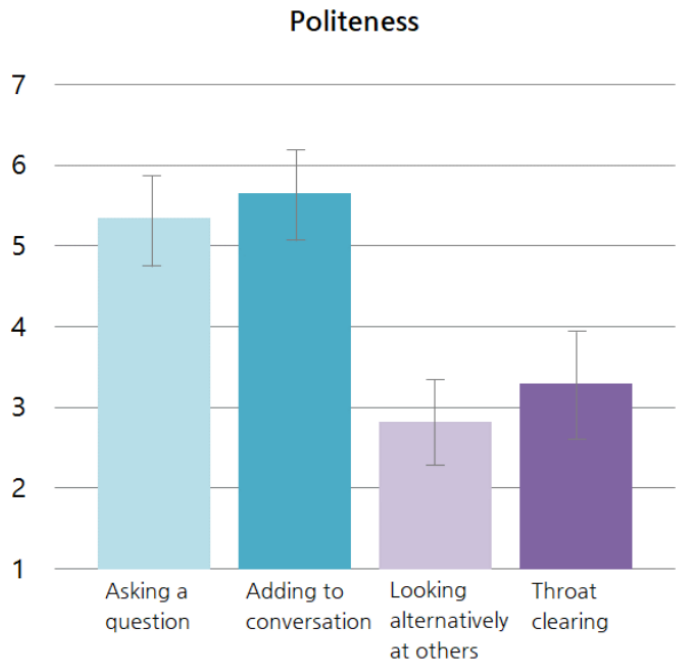

Figure 3.5 Perceived politeness depending on combinations of robot behaviors. The error bar means standard error.

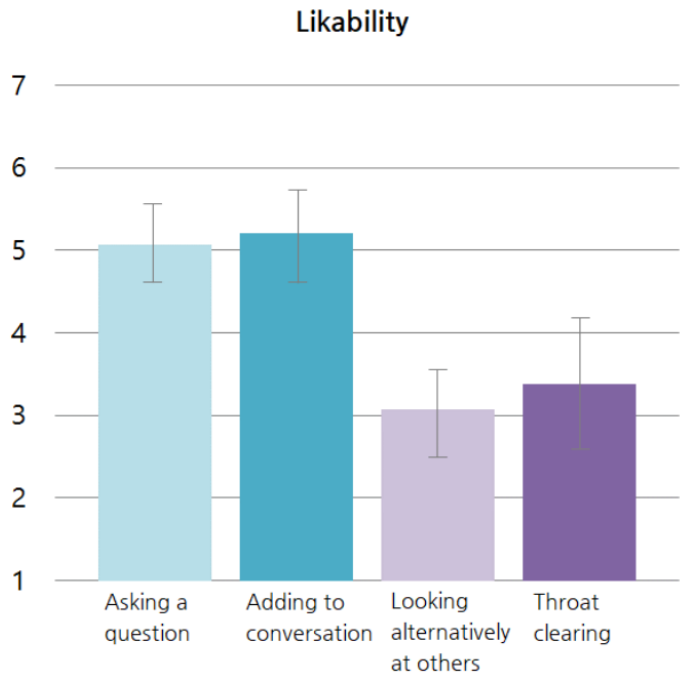

Figure 3.6 Perceived likability depending on combinations of robot behaviors. The error bar means standard error.

3.2.2 Measuring Temperature

The assessment of the robot's safety varied according to combinations of robot behaviors ($t = 2.29$, $p < .05$). The participants assessed the robot's safety as higher when the planning included indirect touch by a thermometer ($M = 4.11$, $SD = 1.43$) than direct touch with its hand ($M = 3.52$, $SD = 1.43$).

The assessment of the robot's knowledgeability varied according to combinations of robot behaviors ($t = 3.57$, $p < .001$). The participants assessed the robot's knowledgeability as higher when the planning included indirect touch by a thermometer ($M = 5.11$, $SD = 1.43$) than direct touch with its hand ($M = 4.10$, $SD = 1.43$).

There was no significant effect on empathy according to combinations of robot behaviors ($t = 1.57$, $p = .135$). There was no significant effect on sociability according to combinations of robot behaviors ($t = 1.51$, $p = .150$).

3.2.3 Design Implications

To streamline the process of designing robot behaviors, we propose a research-based design toolkit and a flowchart for initiating engagement in healthcare settings. Based on the results, a design guideline was suggested. Figure 3.7 shows a flowchart to decide robot behaviors to initiate engagement in healthcare settings. If we can collect enough data of human evaluation on behavioral plannings of a robot, highly evaluated robot behaviors can be prioritized with the larger weight value. Therefore, a robot can try initiating engagement with the first prioritized behavior. Then, if we can recognize a human's appraisal of the robot and if the appraisal is positive, it might be appropriate timing for the robot to perform tasks. If the appraisal is negative, it might be better for the robot to try the next prioritized behavior. If a human's appraisal is not positive after trying the behaviors, the robot can consider ending the interaction.

Also, this design guideline can be used with an HRI scenario design toolkit [67]. Kang, Kim, and Kwak (2018) suggested the research-based design toolkit. The toolkit is composed of four types of physical cards, which are human base cards, human case cards, robot base cards, and robot case cards. Each base card shows a nonverbal behavior graphically. Each case card includes descriptions of possible cases of human behaviors and robot behaviors based on research results. By combining human and robot cards, HRI researchers can create HRI scenarios and possible behavioral decision-makings of a robot.

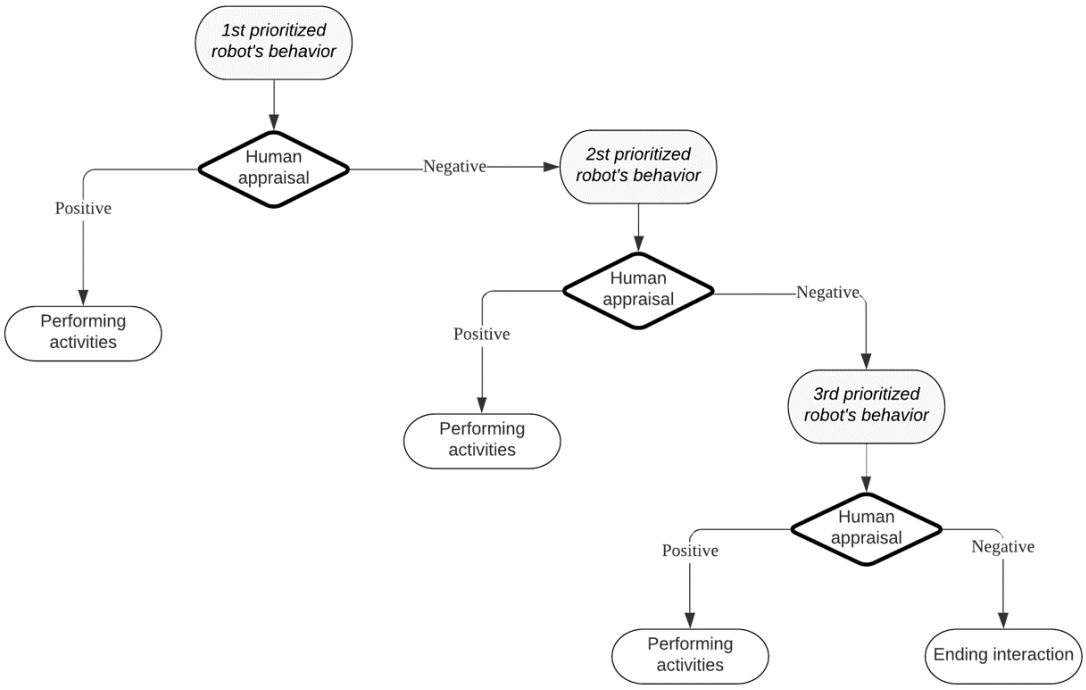

Figure 3.7 Design guideline for deciding robot behavior to initiate engagement in healthcare settings.

Therefore, if we collect a database of possible behaviors in HRI and prioritize behaviors in each social situation of healthcare settings, it is expected to increase engagement by deciding appropriate robot behaviors. It will improve the quality of healthcare services.

3.3 Discussion

In this research, two experiments were conducted to find what kinds of behavioral plannings can be used for a robot to initiate engagement in healthcare settings. The first hypothesis was that combinations of human behaviors can be used as behavioral plannings of a robot to initiate engagement in healthcare settings. The second hypothesis was that depending on situations, different behavioral planning of a robot will be preferred in healthcare settings. To find an answer to the question and to verify the hypothesis, we designed survey-based experiments in two different situations and collected human evaluations on the behavioral plannings of a robot. Based on the results of the experiments, we were able to answer the questions.

Specific behavioral plannings were selected from human behaviors, and they could be used for a robot to initiate engagement in healthcare settings. With the results, we suggested a design guideline for deciding robot behaviors in healthcare settings.

When the robot tried joining two people's conversation, perceived sociability, intelligence, politeness, and likability of the robot were high when the planning included a behavior in the following order: adding to the conversation, asking a question, throat clearing, and looking alternately at others. Adding to the conversation and asking a question are verbal behaviors, while throat clearing and looking alternately at others are nonverbal behaviors. According to the results, it can be inferred that tested verbal behaviors are more suitable for initiating engagement than nonverbal behaviors in the situation where two people are already engaging in conversation. This result is different from previous research that found nonverbal behavior is effective when a robot initiated a conversation [122]. Satake et al. found that when a robot started speaking right away, people thought it is impolite or they did not respond to the robot's voice in a shopping mall. In contrast, this study showed that verbal behaviors were more preferred in the situation. This result indicates that a robot's behavioral plannings can vary depending on situations and contexts. Also, when two people are talking to each other, clear indications might be required for a robot to induce engagement of human participants. It may also be a possibility that the specific robot, which was used in the experiment, was more clearly perceived when it used verbal behaviors rather than nonverbal behaviors because the robot is small in size. Therefore, adding to the conversation and asking a question were more appropriate to initiate engagement in the situation. These behaviors can be prioritized when creating robot behaviors in a similar situation.

When the robot tried measuring temperature, perceived safety and knowledgeability of the robot were higher by indirect touch with a thermometer than by touching directly with its hand. The perceived empathy and sociability of the robot were not significantly different depending on the plannings. It suggests that people might prefer keeping a distance and allow direct physical touch by a robot only if the robot is safe enough. Also, when a robot can use a tool, it might look more knowledgeable. As the items of knowledgeability included reliability, usefulness, and trustworthiness of the robot, highly evaluated safety and knowledgeability might be related to allowing the distance and touch. Therefore, using a thermometer was a more appropriate behavior to initiate engagement in the situation where the evaluators were not familiar with the robot. In a similar situation, using a tool by a robot can be tried first with a user.

More importantly, this research was to explore a part of the conceptual framework to propose a conceptual model. We particularly explored two components of the model, which are robot behavior and human appraisal. Regarding the robot behavior component, it was possible to apply human behaviors to a robot. Also, we investigated which behavior is more preferred to initiate engagement after showing approaching, eye contacting, or verbal greetings. Therefore, the combinations of behaviors might be applied as a social signal for a robot to initiate engagement. Regarding the human appraisal component, we adopted survey-based experiments to collect evaluation data. The evaluation was changed depending on the robot's behaviors. However, we were not able to investigate the direct connection between robot behavior and human mood, and between human mood and human appraisal. As mood is not clearly expressed, we used questionnaires which ask feeling or impression on the robot. Although this research has a limitation, it shows the potential of designing robot behaviors based on the suggested framework in various situations of healthcare settings.

Chapter 4

Engagement in Robot-Assisted Therapy

This chapter covers the second research question to explore how to recognize human social signals to maintain engagement in robot-assisted therapy for children with ASD. The research question and hypotheses are as follows.

RQ 2. What kinds of behavioral factors affect the occurrence of prosocial behaviors toward a robot in robot-assisted therapy?

H 2-1. There will be a positive relationship between human smiles and prosocial behaviors toward a robot in robot-assisted therapy.

H 2-2. After a robot's movement, a series of behaviors of each child will be observed in robot-assisted therapy.

H 2-3. The series of behaviors will be represented by conditional probability in robot-assisted therapy.

H 2-4. The series of behaviors will predict the occurrence of prosocial behaviors toward a robot in robot-assisted therapy.

First, we explored the relationships between human smiles and prosocial behaviors toward a robot. As it has been reported that smiles and prosocial behaviors can be related [21, 49, 137, 144], we investigated whether smiles could be a signal of engaging in prosocial behaviors toward a robot. If we find a positive relationship, we can explore other behavioral factors which affect the occurrence of prosocial behaviors toward the robot. The concurrent or subsequent behaviors might be analyzed as a social signal to indicate the next engagement in prosocial behaviors. The series of behaviors after smiling will be covered in chapter 5. Here, we focus on the first step of exploring the research question by investigating the relationships between human smiles and prosocial behaviors toward a robot.

Prosocial behaviors are behaviors which benefit others [147]. In this research, prosocial behaviors were defined as (1) helping a robot to walk, and (2) helping the robot stand up after it fell down. These prosocial behaviors were selected in robot-assisted therapy based on developmental progress. The development of action-based prosocial behaviors might be the basis of emotion-based prosocial behaviors and empathic behaviors [28, 82]. Although the developmental sequence and timing were various in previous studies, it has been reported that children with ASD can show prosocial behaviors. Action-based prosocial behaviors, such as picking up and returning items someone has dropped, have been observed in children with ASD between 24 and 60 months of age [82]. Also, emotion-based prosocial behaviors, such as responding to others' negative emotions, were reported in a study of 6- and 7-year-old children with ASD [28]. Prosocial behaviors have been investigated with adult participants in combination with positive moods, and smiles were considered as an indicator of positive moods [9, 24, 31, 40]. It suggested that when they smile, people tend to engage in prosocial behaviors. Participants in the previous studies were willing to pick up a dropped pen, to give change for a dollar, and to play a game cooperatively. In this research, we explored whether this chain of behaviors is observed from children toward an NAO robot, which might facilitate prosocial behaviors of children with ASD to support others.

This study explored whether smiles and prosocial behaviors of children are related in robot-assisted therapy, and when the appropriate timings are to arouse smiles for facilitating the engagement. If the hypothesis is supported, it indicates that we might facilitate engagement in prosocial behaviors of a child with ASD toward a robot by arousing smiles. This research particularly investigated the relationships between specific timings of smiles and the two types of prosocial behaviors. If we find a positive relationship between a specific timing of smiles and prosocial behaviors, it suggests when to arouse smiles by a robot. Also, if the related timings of smiles are different in the walking and falling situation of the robot, we need to arouse smiles in different timing of interaction. It suggests that different types of prosocial behaviors might require different timings of affective interactions. Additionally, if we find differences between children with ASD and typically developing (TD) children, it indicates that we need to arouse smiles considering the characteristics of children groups.

4.1 Methods

To explore the research question, we adopted video analysis and a physiological signal-based method in a therapeutic setting for children with ASD. The advantage of video analysis is that we can observe and review simultaneous behaviors from multiple perspectives [51]. To analyze the smiles and prosocial behaviors of each participant, we observed and annotated dynamic behaviors and interactions from recorded videos. However, video analysis has limitations to provide comprehensive information on participants' smiles. The main disadvantage is that video cameras cannot continually capture the faces of participants, depending on their angles and positions. As prosocial behaviors involve frequent movements, we used a wearable device with non-intrusive electromyogram (EMG) sensors. Compared to other sensors, such as electrodermal activity sensors or electroencephalography, EMG sensors can be directly attached to facial muscles to detect smiles [48, 85]. The recorded EMG was used to measure the unobserved smiles of participants during interactions with a robot.

4.1.1 Participants

We recruited eighteen children identified as having mild to moderate levels of ASD through the Institute for Developmental Research of the Aichi Human Service Center in Japan. For comparison, fourteen TD children were recruited. Children with ASD participated in four sessions, and TD children participated in three sessions of robot-assisted activities directed by a therapist. Due to the limitations involved with making the robot fall, we were not able to include all the participants and all the sessions. For the exploratory study, two sessions of six children with ASD and one session of six TD children were selected as they included both walking and falling situations of the robot. Therefore, the final analyses were conducted with data from six children with ASD and six TD children in this study. The average age of six children with ASD (four boys and two girls) was 9.67 years old (6-16, SD = 3.50) and the average age of six TD children (three boys and three girls) was 9.83 years old (6-11, SD = 2.04) All twelve children did not show any concerns about interacting with a robot and wearing a device. This research was approved by the Ethical Committee based on the Declaration of Helsinki and ethical rules established by the Aichi Human Service Center. This research was conducted in an intervention room of the same institute in compliance with the ethical principles. All caregivers

of the children agreed to written informed consent and participated in the entire session.

4.1.2 Robot

An NAO robot was adopted to create social situations. It is a small-sized (58 cm in height) humanoid robot (SoftBank Robotics Corp., Paris, France). NAO has been applied for therapy, rehabilitation, and education contexts requiring interactions with humans [62, 111, 134]. As each child with ASD has various difficulties in communicating and interacting with others [6], a robot can be a therapeutic tool to make each child practice social skills directly with the robot [19, 20, 106]. Compared to traditional therapy methods, such as video modeling and animal therapy, a robot can be used for various situations, including falling. Also, it can communicate by expressing verbal and nonverbal behaviors. The 26 joints in the head, arms, legs, and pelvis of an NAO robot enable it to perform various motions, such as walking, sitting, and grasping. However, the movements are inflexible and unbalanced compared to its human peers, which could lead children to perceive the robot as a care-receiver. After considering the functions and limitations of the NAO robot, we chose "walking with the robot" as the social context for this study. The expected social situations in the given scenario were (1) the robot walking, and (2) the robot falling; the desirable prosocial behaviors we looked for from the children were (1) helping the robot to walk, and (2) helping the robot stand up after it falls down.

The NAO robot was controlled using a teleoperation method. In this study, we used the Wizard of OZ technique, which is a research method to make participants feel that they are interacting with an autonomous system [114]. This method has the advantage to create real-time interactions. A human operator observed each child's responses to the NAO robot in the observation room and controlled the robot's movement by following the cues from a therapist. The voice function of the robot was not used to create simplified interactions and to focus on nonverbal behaviors which can affect prosocial behaviors.

4.1.3 Apparatus

To analyze smiles and behaviors of each participant, video cameras and a wearable device, called Smile Reader, were used in this research (Figure 4.1 and Figure 4.2). Four video cameras were installed on the ceiling of the intervention room. A therapist traced and captured each participant's movements with a handy video

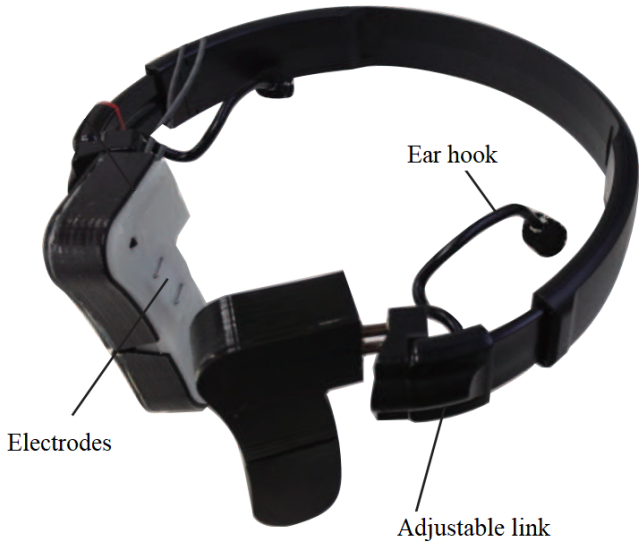

Figure 4.1 Smile Reader which was used in the robot-assisted therapy.

camera. Smile Reader was used to record surface EMG from the facial muscles [48]. The device was attached to both sides of the face of the participants.

We used the wearable device with EMG sensors because the device was designed and developed for smile detection [48]. This device can detect the contractions of facial muscles related to smiles, which are the orbicularis oculi and zygomaticus major. These facial muscle areas have been researched with EMG sensors to measure specific smiles which show spontaneous and positive emotions [42, 66, 89, 107]. Compared to other physiological sensors, such as electroencephalography and functional MRI, facial EMG can be attached directly to the facial muscles related to smiles [85]. Also, it can be used both in laboratory settings and therapy settings. Furthermore, the performance evaluation of the Smile Reader has been investigated with both adults in a laboratory and children with ASD in therapy, and the accuracy of smile detection was reliable [43, 48, 56, 55].

In this research, each participant's facial EMG was recorded with the Smile Reader including four fairs of active electrodes and a BioLog (S&ME, Japan), which is a portable EMG logger including an amplifier. The devices were connected to a laptop wirelessly and EMG signals were recorded in real-time. To synchronize video and EMG data, a noticeable sign was included in the recorded EMG by using a time tagger.

Figure 4.2 A child wearing Smile Reader in the intervention room captured by video cameras.

In this research, each participant's facial EMG was recorded with Smile Reader including four fairs of active electrodes and a BioLog (S&ME, Japan), which is a portable EMG logger including an amplifier. The devices were connected to a laptop wirelessly and EMG signals were recorded in real-time. To synchronize video and EMG data, a noticeable sign was included in the recorded EMG by using a time tagger.

4.1.4 Procedure

The research was conducted to assist a therapist with an NAO robot for children with ASD. Children with ASD participated in this research during the therapy. TD children who joined this research experienced the same procedure. Each child participated in a session every two to three weeks. Each session lasted for 20 to 30 minutes. Every child was allowed to interact with the robot, a parent, or a therapist without restriction during all sessions. The 9.6m^2 area where each child could interact with the robot was fenced for safety (Figure 4.3). Their behaviors were recorded by ceiling cameras and a therapist's camera. Each therapy session was divided into four stages, and each stage included a specific cue from the therapist and the corresponding behaviors of the robot (Figure 4.4). When there were no cues from therapists, the movements of the robot were improvised by a human operator. The improvised behaviors and interactions were not included in analysis. The robot's behaviors during the initiation of interaction were selected considering previous studies of users' evaluations [70, 71].

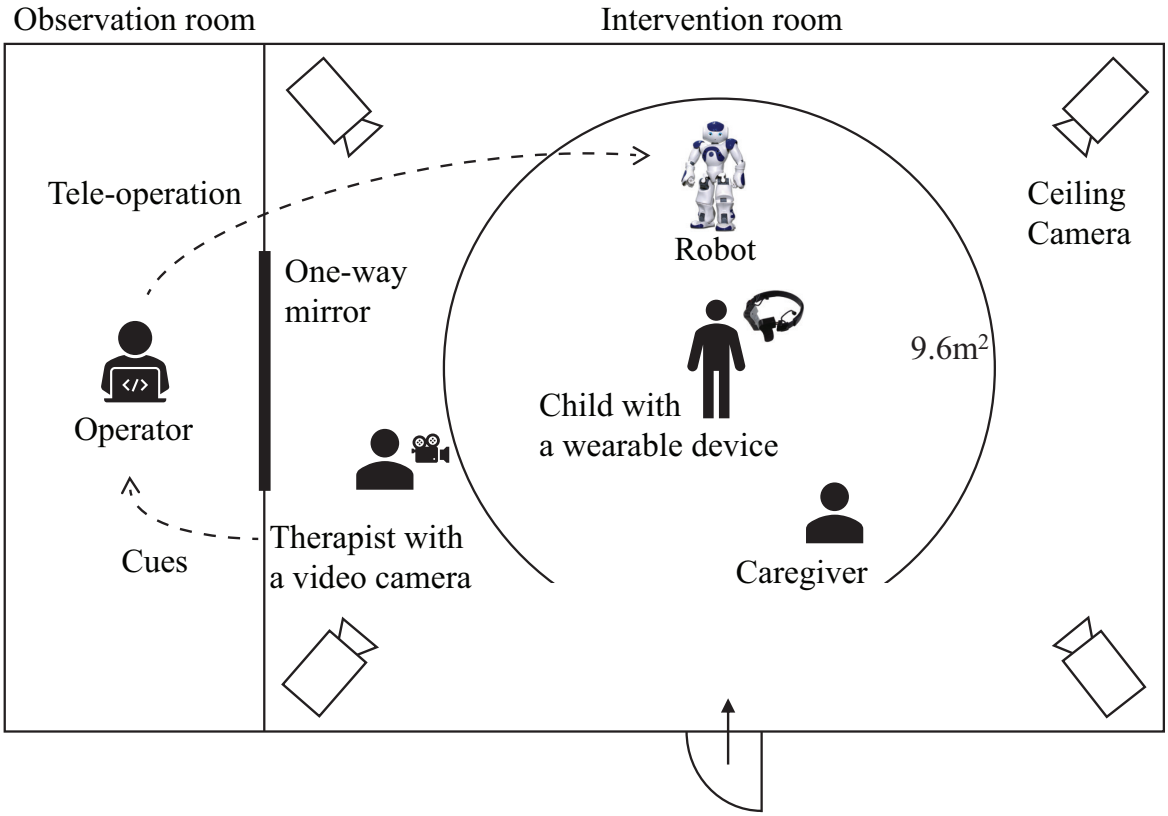

Figure 4.3 Overview of the experimental setting.

The following description of each stage is prescribed procedures. Improvised behaviors or interactions were not included in the data analysis.

Stage 1

In the first stage, each child was introduced to a preparation room. After wearing the device which records facial muscle activities, each child moved into an intervention room with a therapist and parent. The first stage began when the therapist opened the door of the intervention room and pressed a button of a time tagger connected to EMG logging. The therapist introduced each child to the robot, and the robot greeted them by turning its head to look around and moving its arms.

Stage 2

In the second stage, each child interacted freely with the robot. In the middle of this stage, the therapist suggested playing rock-paper-scissors or throwing and receiving small beanbags. NAO used hand gestures and body movements for each game. For

Therapy Stage	Behaviors of NAO Robot	Desirable Behaviors of Children
Stage 1 Greetings	• turning head • moving arms 	• approaching the robot
Stage 2 Play	• gestures and movements for each game  	• playing with the robot
Stage 3 Walking	• nodding • standing up • reaching out arms 	• holding hands • walking
	• (unoperated) falling 	• holding the falling robot • making the robot stand up
Stage 4 Farewell	• waving hands 	• saying good-bye

Figure 4.4 The designed behaviors of NAO and desirable behaviors of children in each therapy stage.

example, during the rock-paper-scissors game, the robot made a handshape of rock, paper, or scissors, and when the robot won, it raised its arms. When the robot lost the game, it looked down and shook its head from side to side. When playing with the beanbags, the robot reached out its hands to receive the beanbags from a child and used its arms to throw them toward the child. Upon failing to catch a beanbag, the robot looked down, raised an arm, and tapped its own head.

Stage 3

In the third stage, the therapist suggested walking together with the NAO robot, and the robot agreed with nodding, standing up, or reaching out with its arms. In this scenario, the desirable behaviors of children included holding hands of the robot, and walking together. When a child did not show any expected behaviors, the therapist or a parent verbally directed the child to help the robot walk. On the other hand, when the robot fell down by chance, the therapist observed each child's spontaneous responses without direction. The desirable expected behaviors of children were those that helped the robot stand up. When a child helped the robot to walk or stand up, the therapist said, "Thank you" to the child on behalf of the robot.

Stage 4

In the last stage, the therapist suggested finishing the session. In response to the therapist's cue, the NAO nodded and waved a hand. After finishing the last stages, each child moved to the preparation room with a parent, and took off the wearable device.

4.1.5 Video Analysis

Video analysis was adopted to measure the duration of smiles and prosocial behaviors. Smiles were defined as changes around the lips or eyes, as facial muscles related to positive affect are contracted by the changes [42, 105]. Prosocial behaviors were defined differently in the two situations. In the walking situation, the prosocial behaviors from children included approaching NAO to hold hand(s) and holding NAO's hand(s), or walking together while holding NAO's hand(s). When a child started approaching NAO to hold hand(s), we identified the point as the starting time of prosocial behavior. Prosocial behaviors during the falling of the NAO robot were defined as approaching NAO to hold the body and making the robot stand up. When the robot was falling in front of a child, holding the falling robot or making the robot stand up were defined as prosocial behaviors. When a child released his or her hold on NAO's hand(s) or body, we identified the point as the ending time of prosocial behavior.

Step 1: Annotating video streams

The video streams were annotated by two trained examiners using Dartfish, which is a tagging software (Dartfish, Fribourg, Switzerland). The annotation included smiles, prosocial behaviors, and other remarkable behaviors of each participant, such as waving hands, talking, and gesturing. The duration of smiles and prosocial behaviors were measured per milliseconds (ms).

Step 2: Selecting segments of video

To measure and analyze smiles and prosocial behaviors, specific segments of the video were selected: (a) one minute after entering the intervention room (encounter with the robot), (b) one minute before starting prosocial behaviors in the walking situation, (c) one minute after starting prosocial behaviors in the walking situation, (d) one minute before starting prosocial behaviors in the falling situation, (e) the

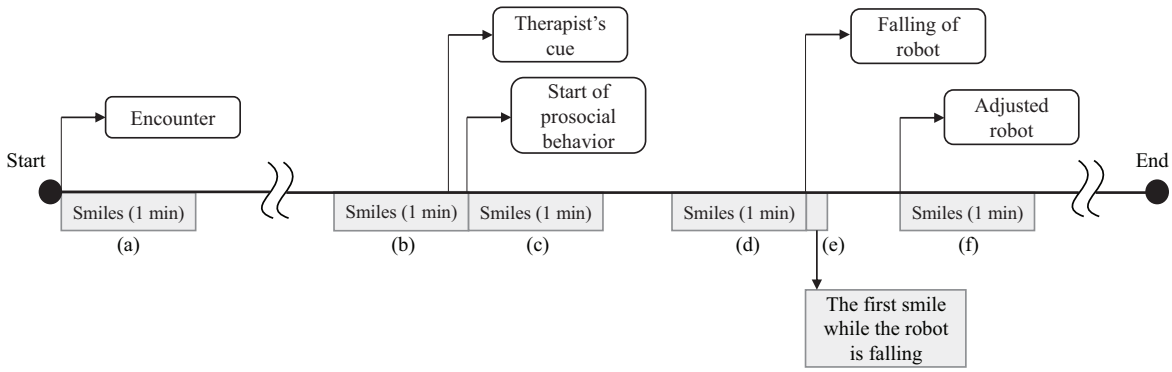

Figure 4.5 Timeline of analyzed parts of smiles.

duration of the first smile when the robot is falling down, and (f) one minute after the robot is adjusted in the falling situation (Figure 4.5). The segments were selected considering specific timings that might affect smiles and prosocial behaviors. (b), (d), and (e) were selected considering that prosocial behaviors occurred more after smiling in previous studies [49, 144]. (a) was selected considering that first impressions might change behaviors toward the robot throughout the session [149]. To confirm that smiles before prosocial behaviors are more related to prosocial behaviors, (c) and (f), which are smiles during or after prosocial behaviors, were selected.

Each length was selected considering the duration of one activity, which lasted at least around one minute. For each participant, the analyzed timings were limited to the first experience of walking and falling of the robot in a session, as each participant experienced a different number and duration of the social situations depending on interactions with the robot.

For the annotation of smiles in selected segments, reliability between the two examiners was high. The average intraclass correlation coefficient was .849 with 95% confidence interval from .811 to .879 ($F(307, 307) = 6.629$, $p < .001$).

Step 3: Calculating the duration

The duration of prosocial behavior was calculated as the amount of time between the starting point and the ending point of the behavior. The duration of smiles was calculated as the amount of time between the starting time and ending time of the facial expression with upward lip corners or downward eye corners.

4.1.6 Signal Processing

To estimate unobserved smiles, we measured the facial EMG signals of each child using four pairs of electrodes. When video cameras could not capture their face because children unexpectedly turned around or stood up, which were frequently included when doing prosocial behaviors, we detected smiles by the following signal processing algorithm. First, 50~350 Hz band-pass filter was applied to extract the EMG signals by removing noise and outliers. Since each EMG signal is a superposition of multiple facial muscle activities, Independent Component Analysis (ICA) was applied to convert the filtered data into four independent signals to increase the saliency of each signal. Then, root-mean-squared averaging was applied to each independent component with a 100 ms averaging window. Finally, an Artificial Neural Network (ANN) was trained using the analysis of human coders as a teaching signal to recognize the unobserved smiles of each participant.

In previous studies, when EMG signals were classified by ANN, the results showed higher accuracy than other classification methods, such as Support Vector Machine [83, 100]. Smile Reader also showed high accuracy with ANN [48, 55]. When an ANN was applied to detect positive facial expressions with Smile Reader, the average Kappa Coefficient between human coders and the classifier was 0.95 [48], which shows highly identical inter-rater agreement. Therefore, we applied the ANN classification to detect the unobserved smiles of each participant. This signal processing was performed by MATLAB R2017b (Mathworks, USA).

4.2 Results

The selected video segments were described quantitatively to observe behavior changes and a possible relationship between smiles and prosocial behaviors.

4.2.1 Unobservable Smiles and Estimation with EMG

The smiles presented in this section are complemented durations with smiles detected by the EMG signal processing, as there were unobservable smiles. The ratio of unobservable parts in a whole session was a minimum of 2% and a maximum of 25% for a child with ASD, and a minimum of 3% and a maximum of 14% were a TD child. We used the EMG recordings from the wearable device to estimate smiles during the fragments unobservable with the video data. Based on this estimation, the duration of smiles was calculated and compared with the duration of smiles without EMG

Table 4.1 The averaged smiles in the first and second session of children with ASD (unit is seconds).

ASD Session 1 Smile Duration Mean ± SD	ASD Session 2 Smile Duration Mean ± SD	Timing
23.7 ± 17.9	24.9 ± 20.1	one minute after entering the intervention room
20.2 ± 12.9	24.6 ± 11.1	one minute before walking with the robot
35.5 ± 16.8	19.6 ± 15.2	after starting walking together for one minute
28.1 ± 11.9	24 ± 10.1	one minute before falling of the robot
7.7 ± 4.3	9.7 ± 4.3	while the robot was falling down
43 ± 10.1	17.8 ± 8.7	one minute after the fallen robot was adjusted

data. The classification result ranged from 51% to 88% accuracy for each child, and the overall average accuracy was 70%. Accuracy was calculated by cross-validation in machine learning. Among data of smile and no-smile, datasets having less noise and artifacts were used for training to evaluate the predictive performance on the testing set. All results presented below are obtained from combined durations with the observable segments by video data and the unobservable segments by EMG data. We verified that none of the presented trends changed with the estimation of the EMG data.

4.2.2 Smiles and Prosocial Behaviors in the Walking Situation

On average, the duration of smiles and prosocial behaviors in children with ASD increased in the second session compared to the first session (Table 4.1 and Figure 4.6). Particularly, the duration of smiles after entering the intervention room and before walking together increased in the second session of children with ASD.

On the other hand, TD children showed shorter smiles than children with ASD throughout the session, but they did prosocial behaviors longer than children with ASD (Table 4.2 and Figure 4.7). TD children smiled the most when they entered the intervention room, and then smiled less.

Each child with ASD showed different changes in the second session. Figure 4.8 indicates relationships between the duration of smiles and the duration of prosocial behaviors in the walking situation from each participant. The duration of smiles is the sum of smiles during the encounter and before walking together with the robot, as shown in (Figure 4.5 (a) and (b)), which increased in the second session. Duration of prosocial behaviors is the sum of helping the robot walk. Empty symbols signify the first session and filled symbols signify the second session. The

Table 4.2 The averaged smiles in the first session of children with ASD and TD children (unit is seconds).

ASD Session 1 Smile Duration Mean ± SD	TD Session 1 Smile Duration Mean ± SD	Timing
23.7 ± 17.9	20.4 ± 15.6	one minute after entering the intervention room
20.2 ± 12.9	8.5 ± 4.9	one minute before walking with the robot
35.5 ± 16.8	16.6 ± 16.3	after starting walking together for one minute
28.1 ± 11.9	17.7 ± 15.3	one minute before falling of the robot
7.7 ± 4.3	2 ± 3.5	while the robot was falling down
43 ± 10.1	10.4 ± 7.8	one minute after the fallen robot was adjusted

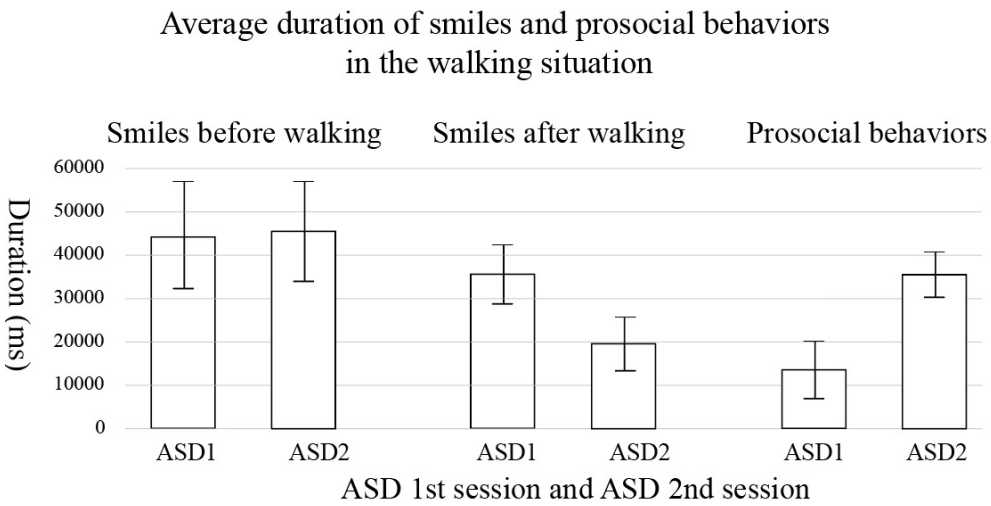

Figure 4.6 The average duration of the smiles and prosocial behaviors in the first session of children with ASD and TD children with the estimated smiles from EMG.

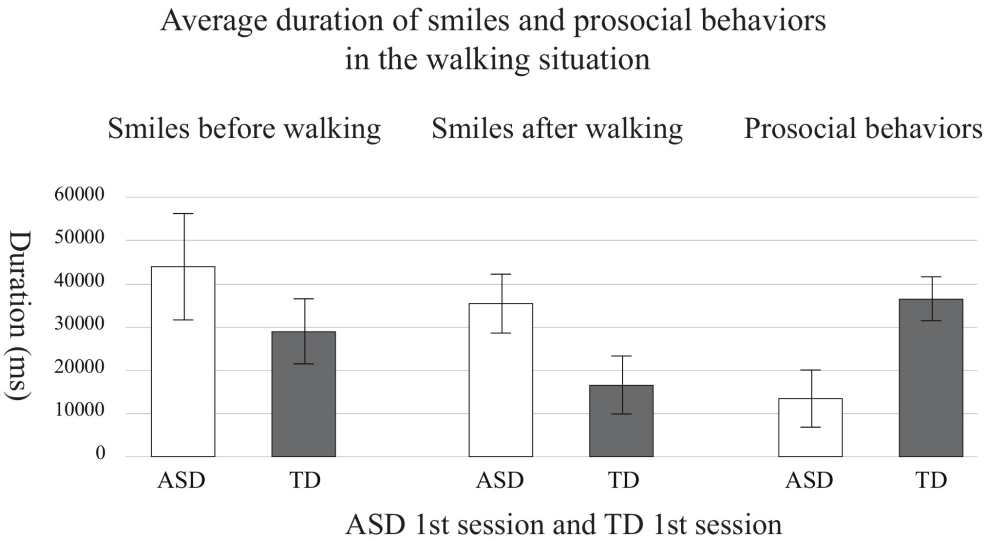

Figure 4.7 The average duration of the smiles and prosocial behaviors in the first session of children with ASD and TD children with the estimated smiles from EMG.

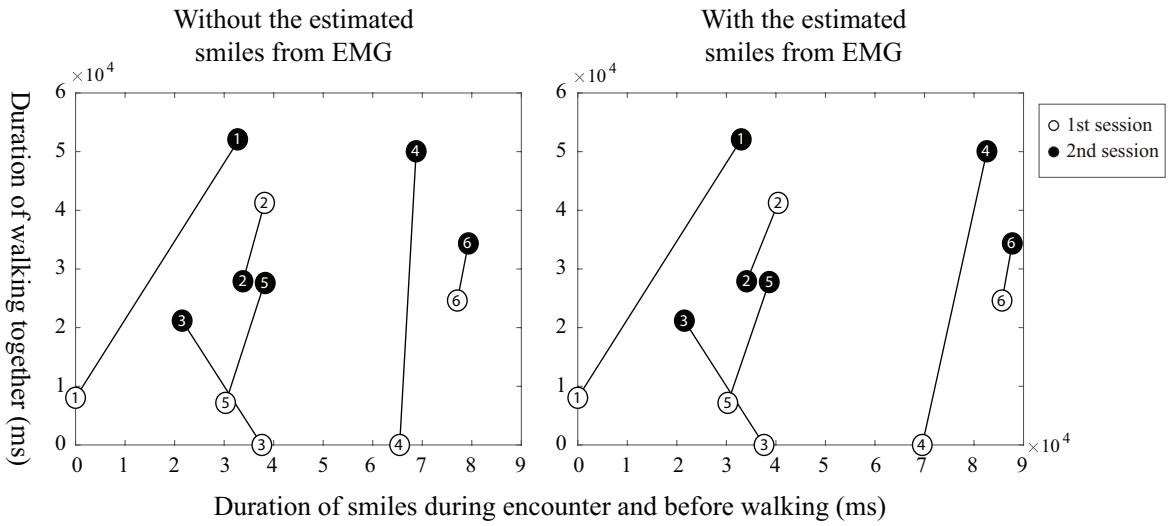

Figure 4.8 The trend between smiles and prosocial behaviors of each child with ASD in the walking situation.

numbers in the symbols indicate the participant number of each child with ASD. Four children (ASD-P1, ASD-P4, ASD-P5, and ASD-P6) out of six children with ASD showed a longer duration of smiles and longer prosocial behaviors during the second session than during the first session. One child (ASD-P2) showed a shorter duration of smiles and a shorter prosocial behavior during the second session than in the first session. Another child (ASD-P3) showed an increased duration of prosocial behaviors but showed a decreased duration of smiles in the second session. Instead, the child started to sing a song before doing prosocial behaviors. The results imply the possibility of a positive correlation between smiles and prosocial behaviors in children with ASD.

4.2.3 Smiles and Prosocial Behaviors in the Falling Situation

On average, children with ASD smiled longer than TD children when the robot was falling down (Table 4.2). All children with ASD smiled at the robot during the falling moment in the first and second session. Among them, two children with ASD (ASD-P2 and ASD-P6) showed prosocial behaviors in the first session. Three children with ASD (ASD-P1, ASD-P2, and ASD-P5) showed prosocial behaviors in the second session. In contrast, three TD children (TD-P1, TD-P2, and TD-P5) did not smile while the robot was falling down. Among TD children, one child (TD-P4) immediately helped the robot stand up. Two TD children (TD-P2 and TD-P6) helped the robot after watching the fallen robot for approximately 10 seconds.

On the other hand, the duration of smiles before and after the falling situation decreased in the second session (Table 4.1). Before falling of the robot, children with ASD smiled less than in the first session. Likewise, after the fallen robot was adjusted, children with ASD smiled less than in the first session.

4.3 Discussion

We investigated what kinds of behavioral factors affect the occurrence of prosocial behaviors toward a robot in robot-assisted therapy. Particularly, the hypothesis we explored in this chapter was that there will be a positive relationship between the smiles of each child and prosocial behaviors toward a robot. We explored whether smiles are a potential key factor affecting prosocial behaviors toward the robot. To answer the research question and to verify the hypothesis, we recorded the video and EMG of each participant and calculated the duration of smiles and

prosocial behaviors in specific timings. With the calculated duration, we explored relationships between smiles and prosocial behaviors in robot-assisted therapy by using descriptive analysis. The main findings are as follows.

First, there were changes in the smiles and prosocial behaviors of children with ASD. In the second session, the duration of smiles and prosocial behaviors increased on average. In particular, the duration of smiles increased when entering the intervention room, before walking, and while the robot was falling down. On the other hand, the duration of smiles during prosocial behaviors decreased. A possible reason for the decrease is that the children tried to concentrate on walking with the robot, which would relate to increased cognitive load caused by a limited working memory [69]. In the falling situation, three children with ASD showed prosocial behaviors in the second session. They smiled more than in the first session when the robot was falling. Other children who showed a shorter duration of smiles in the second session did not help the robot. It indicates that smiles before prosocial behaviors might be related to prosocial behaviors.

Second, there were behavioral differences between children with ASD and TD children in two social situations. Overall, children with ASD smiled more and exhibited fewer prosocial behaviors than TD children. Children with ASD easily responded to the robot's movements by smiling or moving their bodies. On the other hand, TD children smiled the most during the first moment with the robot and then smiled less and less. This result might indicate that TD children lost interest in the robot after the first encounter. Otherwise, it is possible that they showed fewer smiles, but they maintained a positive mood longer than children with ASD. On the contrary, smiles just before prosocial behaviors were positively related to prosocial behaviors of children with ASD. It suggests that an interaction with a robot can induce immediate behaviors in children with ASD.

Another difference between children with ASD and TD children was the head direction in the falling situation. While all children with ASD continuously headed toward the robot after the robot fell down, all TD children headed toward their caregiver or a therapist. It should be noted that the falling of the robot occurred unexpectedly and did not include a therapist's cues providing additional directions. Hence, the observation that these children responded to the falling by heading toward an adult can be explained by typical social referencing [27]. TD children tend to refer to the verbal and nonverbal behaviors of a parent or a caregiver in unfamiliar social situations. In this research, TD children required directions or confirmations from adults in the falling situation. On the other hand, four out of six children with

ASD did not look at a parent or therapist after seeing the falling of the robot. It suggests that when they engaged in prosocial behaviors in the falling situation, there was a high possibility of doing the behaviors voluntarily.

However, there were several limitations in this research. First, the number of sessions and cases was limited. Although children with ASD participated in a total of four sessions, and TD children participated in a total of three sessions, the maximum sessions for this research included two sessions with children with ASD and one session with TD children. Due to this limitation, statistical tests including correlation analysis between the groups could not be performed. Instead, we observed a trend of positive relationships. In addition, some of the children with ASD experienced more therapy sessions between the two selected sessions, and this might have affected the results. Therefore, data availability for research should be considered when selecting the types of prosocial behaviors in the next research.

Also, the walking situation included additional direction from the therapist or parent. On the other hand, children were not guided when the robot fell down. This unequal condition could have affected the behaviors of children. Although the condition revealed voluntary and guided prosocial behaviors of participants, baselines of behavioral measurements should be considered in future experiments. To figure out the effect of this factor, the Bayesian model will include prompting by a therapist or a parent as a predictor of prosocial behavior.

Another purpose of this research was to explore a part of the conceptual framework. We particularly explored two components of the model, which are facial expression and subsequent behaviors of humans. We focused on smiles as an indicator of positive affect and prosocial behaviors as a related behavior with smiles. In this research, we observed a trend of the positive relationship between specific timings of smiles and prosocial behaviors. Prosocial behaviors might be facilitated right after smiling. However, we were not able to conduct statistical tests due to the sample size. Also, we were not able to investigate the direct connection between a human appraisal and facial expression, as the appraisal is not recognizable. Although this research has a limitation, we observed a trend of the positive relationship between smiles and prosocial behaviors, and it shows the potential of facilitating engagement in prosocial behaviors by recognizing smiles.

Chapter 5

Modeling Robot Behaviors for Facilitating Engagement

In the previous chapter, we explored a possible positive relationship between smiles and prosocial behaviors in robot-assisted therapy. However, the results do not indicate that the NAO robot's behaviors triggered smiles. We need to consider the possibility of increased smiles due to interactions with a therapist or a parent. Also, we did not explore possible series of behaviors after smiling, which can be a social signal of engaging in prosocial behaviors. Thus, this chapter is to explore the representation of social signals engaging in prosocial behaviors, and the second question is investigated with different hypotheses.

RQ 2. What kinds of behavioral factors affect the occurrence of prosocial behaviors toward a robot in robot-assisted therapy?

H 2-2. After a robot's movement, a series of behaviors of each child will be observed in robot-assisted therapy.

H 2-3. The series of behaviors will be represented by conditional probability in robot-assisted therapy.

H 2-4. The series of behaviors will predict the occurrence of prosocial behaviors toward a robot in robot-assisted therapy.

To answer the research question and to verify the hypotheses, first, we observed detailed behaviors of each child before they engage in prosocial behaviors. Second, a common series of behaviors followed by prosocial behaviors were investigated from the behavioral data of each participant. Third, we represented the probability of a series of behaviors by creating a Bayesian model. Lastly, we validated the accuracy of the model with leave-one-out cross-validation.

If the hypothesis is supported, it indicates that we could create a prediction system of a robot based on smile analysis. This system is expected to anticipate a sequence of behaviors, which are considered as a social signal, and calculate a probability of engaging in prosocial behaviors. This finding could be applied to personalized robot-assisted therapy for individuals with ASD. With the prediction system, a robot can decide a timely and appropriate behavior to facilitate each child's engagement in prosocial behaviors. By detecting smiles and subsequent behaviors, it could be possible to anticipate whether a child will engage in prosocial behaviors toward the robot. If the probability of engaging in prosocial behaviors is less than 50%, the robot might facilitate the engagement by arousing more smiles. Therefore, smile-based prediction and designing the next robot behaviors can be a feasible framework for personalized robot-assisted therapy. Also, this framework can be extended to facilitate engagement in other smile-related behaviors.

In this research, this Bayesian model will be integrated into a conceptual model for long-term engagement. The suggested models will have implications for designing robot behaviors in healthcare settings.

5.1 Methods

The process of modeling was based on the data of observed human behaviors after a robot's movement. From the data, we found patterns by identifying a series of behaviors. After that, we analyzed a probabilistic relationship of the identified factors. The final step of the modeling was creating a Bayesian model which describes the behavioral factors. Video analysis was adopted to observe possible behavioral factors which affect the occurrence of prosocial behaviors toward a robot. Participants and data set were the same as those described in Chapter 4.

To observe detailed behaviors between an NAO robot and a child, ten seconds of videos were selected. The selected fragments were before walking with the robot and during the falling down of the robot, which are the timing before engaging in prosocial behaviors. We transcribed the head direction, facial expression, and body movement of each child and robot to observe informative nonverbal behaviors [46]. The purpose of this video analysis was to determine behavior changes before engaging in prosocial behaviors. There were three main questions for the observation. First, what triggers smiles? Second, what are the concurrent or subsequent behaviors with smiles? Third, are these behaviors linked to prosocial behaviors of children after watching the movements of an NAO robot?

We observed the behaviors of each child from a total of 36 cases of robot walking and falling situations. Video and EMG data of children with ASD in the first and second sessions and of TD children in the first session were included to observe a common series of behaviors. The common behaviors were identified by dividing the cases into four groups.

5.2 Results

To investigate how behaviors change after the robot's movements and find a common series of behaviors before engaging in prosocial behaviors, we observed behaviors of each participant ten seconds before prosocial behaviors. If smiles are observed and other behaviors follow after the smile, we might predict the behaviors after observing smiles. Also, if smiles are triggered by a robot, we might arouse smiles timely and facilitate prosocial behaviors with a robot.

The observation was based on a total of 36 cases of robot walking and falling situations. It included 12 cases of children with ASD in the first session, 12 cases of children with ASD in the second session, and 12 cases of TD children in the first session. We observed four types of common cases.

5.2.1 Before Walking of Robot

Case A: Cases of children who showed smiles and prosocial behaviors.

ASD-P1, ASD-P2, ASD-P4, and ASD-P6 showed smiles toward the robot after watching the robot's movements, such as nodding and reaching out its arms. After smiling, they maintained the head direction toward the robot, went closer to the robot, and then showed prosocial behaviors voluntarily. In the case of ASD-P6, the child showed the same pattern of behaviors both in the first and second session.

We found similar interactions from TD-P2, TD-P4, and TD-P5. Children, who smiled and maintained their head direction toward the robot, went closer to the robot and showed prosocial behaviors voluntarily. The smiles were triggered by the robot's movement or observation of interactions between a parent and the robot.

On the other hand, ASD-P2 showed smiles toward the robot after watching the robot's nodding. However, the child's head direction became toward own body and the child started to move own fingers without smiling. When the child was focusing on his fingers, his parents tapped his back two times and suggested walking with the robot. The child looked at his parents and then stood up to hold the robot's hands.

Case B: Cases of children who did not show smiles nor prosocial behaviors.

ASD-P3 in the first session did not smile after watching the robot's nodding and standing up and did not show prosocial behaviors. The robot's movements made the child move the head toward the robot temporarily; however, the child did not maintain the head direction. The child looked at the therapist's camera and made a V shape with fingers in the first session.

Case C: Cases of children who showed smiles but did not show prosocial behaviors.

ASD-P4 in the first session smiled toward the robot after watching the robot's standing up. However, the child did not maintain the head direction. The child started to smile toward the parents and went closer to them.

Case D: Cases of children who did not show smiles but showed prosocial behaviors.

Total eight cases from children with ASD and TD children did not smile after watching the robot's movements, but showed prosocial behaviors. Before doing prosocial behaviors, they received a parent's help or a therapist's additional direction. When the head direction was toward the robot, the child started to follow the direction.

5.2.2 During Falling of Robot

Case A: Cases of children who showed smiles and prosocial behaviors.

In the five cases, children with ASD smiled toward the robot when the robot was falling and then moved closer to the robot. The head direction was continuously directed toward the robot. The children smiled toward the robot before starting prosocial behaviors.

TD-P2, TD-P4, and TD-P6 also showed smiles and prosocial behaviors. However, they showed different aspects of behaviors, which were not observed in children with ASD. TD-P4 and TD-P6 looked at the therapist after doing prosocial behaviors. TD-P2 did not show smiles when the robot was falling. However, the child looked at the therapist after the robot fell and asked the therapist if helping the robot is allowed. And then the child smiled toward the robot before starting prosocial behaviors.

Case B: Cases of children who did not show smiles and prosocial behaviors.

In the six cases, children with ASD released the robot's hands and became distant from the robot when the robot was falling. The head direction was continuously directed toward the robot.

On the other hand, TD-P1 and TD-P3 looked at the therapist after distancing from the robot. TD-P5 watched the robot's falling while sitting behind and holding onto a parent. The head direction of this child was continuously toward the robot, but this child did not show any different facial expressions or body movements after seeing the falling of the robot.

Case C: Cases of children who showed smiles but did not show prosocial behaviors.

ASD-P4 smiled toward the robot when the robot was falling but did not show prosocial behaviors both in the first and the second session. In the first session, the child started to smile while looking around the intervention room and did not move closer to the robot. In the second session, the child smiled toward the robot when the robot was falling, and then continuously smiled toward the robot. However, the child did not move closer to the robot.

Case D: Cases of children who did not show smiles but showed prosocial behaviors.

There were no cases which belong to this.

5.2.3 Bayesian Model

We propose a probabilistic model based on the results of the video analysis. A Bayesian framework was adopted to express the uncertainty of variables and flexibly represent changes in the relationships among variables [99]. In this study, six common behaviors were observed from children with ASD and TD children before engaging in prosocial behaviors toward the robot. The findings are expressed in a flowchart (Figure 5.1).

1. The triggers of smiles were three types. Most children smiled after the robot's movements, such as nodding and reaching out arms. Walking and falling of the robot were also a trigger of smiles. Two children smiled when they started interacting with the robot, such as talking to the robot. One child smiled after

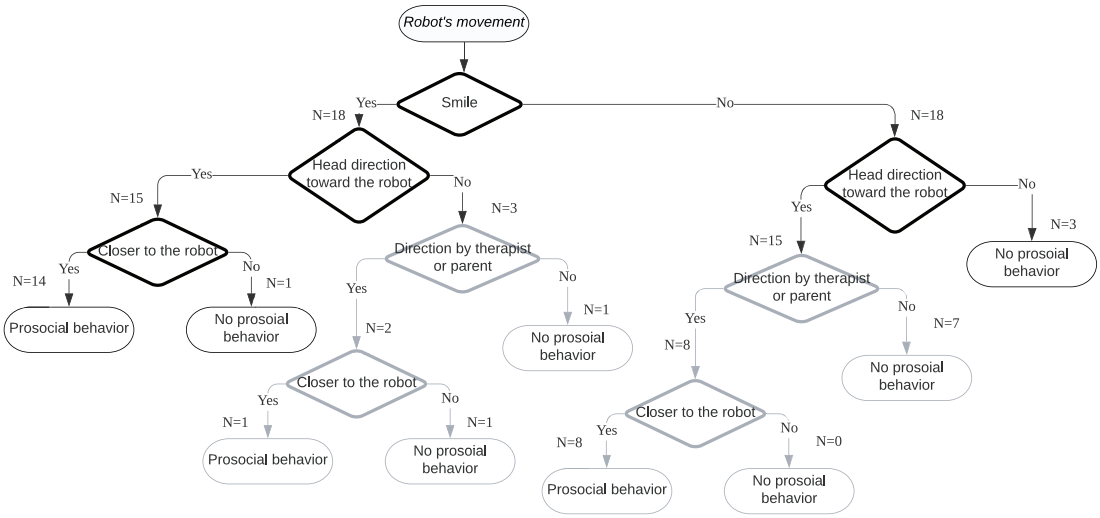

Figure 5.1 A flowchart of a series of behaviors after the robot's movement.

observing an interaction between the robot and a parent. All three types of the trigger are related to experience watching the robot's movements.

2. Smiles towards the robot were followed by heading toward the robot, being closer to the robot, and then doing prosocial behaviors voluntarily.

3. When the head direction was not toward the robot after smiling at the robot, children went closer to the robot and started prosocial behaviors if there were additional directions from the therapist or a parent.

4. When the head direction was toward the robot after no smiling at the robot, children went closer to the robot and started prosocial behaviors if there were additional directions from the therapist or a parent.

5. When a child did not smile toward the robot at any timing after the robot's movement, continuous head direction toward the other person was followed by no prosocial behaviors even if there were additional directions from the therapist or a parent.

6. When a child did not smile toward the robot at any timing after the robot's movement but the head direction toward the robot, keeping distant from the robot was followed by no prosocial behaviors even if there were additional directions from the therapist or a parent.

We observed three types of smile triggers during the robot-assisted activities. Most children smiled after the robot exhibited movements, such as nodding and reaching out its arms. Walking and falling of the robot were also triggers for smiles. The second trigger type was related to the child expecting robot movements. In this research, two children smiled when they started interacting with the robot. The third trigger was observing the robot's movements. One child smiled after looking at an interaction between the robot and a parent.

The three smile triggers in this study were related to experience watching the robot's movements. Therefore, smiling, heading toward the robot, and approaching the robot might be connected factors in the time series with prosocial behaviors. Before ten seconds of doing prosocial behaviors, the three types of behaviors kept changing. However, once a smile was detected, when the head direction was toward the robot, approaching the robot and doing prosocial behaviors occurred. In particular, smiles toward the robot preceded voluntary prosocial behaviors. This observation indicates that if a child shows a smile, and then if the child heads toward a robot and approaches the robot, there is a high probability that prosocial behaviors will be performed.

On the other hand, if a child does not smile, additional direction by a therapist or a parent will help facilitate prosocial behaviors. Otherwise, additional interactions with a robot will be necessary. Such intervention by a parent or therapist may result in further interactions between the child and the robot that trigger smiles. A Bayesian framework can express the relationships between smiling, heading, approaching, and engaging in prosocial behavior.

This Bayesian framework with conditional probability tables represents the relationships among the four variables (Figure 5.2). In the figure, the number of cases is in parentheses. The probability of each node was acquired from the 36 cases of ten seconds before prosocial behaviors. Therefore, the probability of smiles when children showed prosocial behaviors might be used as a prior to predict the likelihood of prosocial behaviors when smiles are observed. This conditional probability can be expressed by Bayes' theorem, as follows:

$$P(PB|S) = P(S, PB)/P(S) \tag{5.1}$$

PB denotes doing prosocial behaviors and S denotes smiling. When the two variables are assumed to be independent, the likelihood of prosocial behavior given a smile can be calculated. From the 36 cases of video analysis, the probability of a smile was 0.5; the probability of prosocial behavior was 0.64. When participants

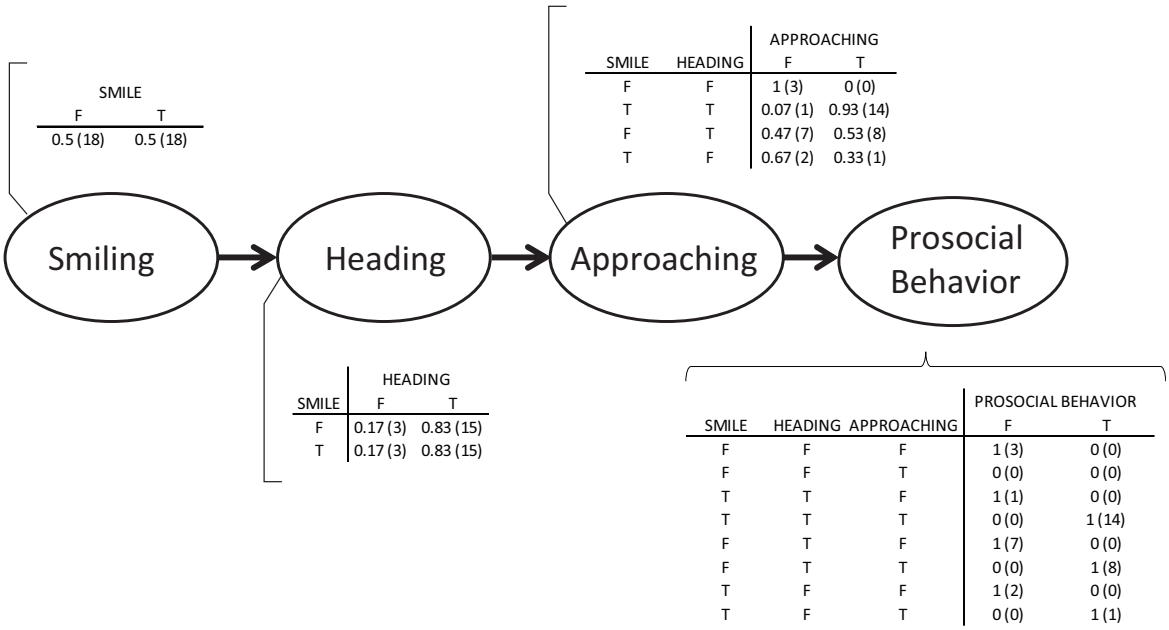

Figure 5.2 A proposed Bayesian network with conditional probability tables.

Table 5.1 Joint probability of smiles and prosocial behaviors from 36 cases of participants.

	Prosocial Behavior		
Smile	Yes	No	Total
Yes	0.42	0.08	0.5
No	0.22	0.28	0.5
Total	0.64	0.36	1.0

did prosocial behavior, the probability of smiles before doing prosocial behavior was 0.42. Table 5.1 shows the joint probability of smiles and prosocial behaviors. It includes both voluntary prosocial behaviors and directed prosocial behaviors by a therapist or a parent. Therefore, we can predict the likelihood of prosocial behavior given a smile:

$$P(PB|S) = 0.42/0.5 = 0.84 \tag{5.2}$$

The likelihood of prosocial behavior given a smile was 84%, only if the probability of prosocial behavior is known, and then the probability of smile before prosocial behavior is known.

$$P(PB|\overline{S}) = 0.22/0.5 = 0.44 \tag{5.3}$$

On the other hand, the likelihood of prosocial behavior given no smile was 44% only if the probability of prosocial behavior is known and then the probability of no smile before prosocial behavior is known. Here, $\overline{S}$ denotes no smiling. In this study, the probability of no prosocial behavior was 0.08 after smiling and the probability of prosocial behaviors after smiling accounted for 66% of the total prosocial behaviors. This result signifies that we could predict prosocial behaviors by analyzing smiles and that we could facilitate prosocial behaviors by arousing smiles. Additionally, among 18 cases that showed smiling, 14 cases showed smiling, heading toward the robot, approaching the robot, and voluntary prosocial behaviors in the time series. Therefore, smiles might be the beginning of a social signal for engaging in prosocial behaviors.

5.2.4 Model Validation

To evaluate the estimation with the Bayesian model, we used leave-one-out cross-validation. With this method, we can validate the model using the small sample, as the collected data can be used for both training and testing [119]. Also, this method can be used to validate the predictive accuracy of the Bayesian model [139]. All the data set was used for training of this model except data from one participant which was used for testing. This process was repeated for all participants one by one with all combinations of the predictors. Then, the accuracy of each predictor was averaged. The selected predictors were prosocial behavior, smiling, heading toward the robot, and prompting by a therapist or a parent. Approaching toward the robot was not selected as a predictor because prosocial behaviors always happened when smiling, heading, and approaching occurred with the sample data. Also, we included prompting in this model considering that the therapeutic setting in this study is to assist the therapist or the parent.

Figure 5.3 and Figure 5.4 show the accuracy of each predictor and the combinations of predictors. S denotes smiling. H denotes heading toward the robot. P denotes prompting by the parent or the parent. + means combinations of two or three predictors.

The results show that the prosocial behaviors of children with ASD and TD children were predicted differently. For TD children, the highest accuracy of prediction was with smiling, heading, and prompting combined as predictors. This indicates that prosocial behaviors could be predicted with over 80% accuracy on average by detecting smiling, heading toward the robot, and then prompting. Only with prompting, the accuracy of prediction was the lowest. However, prosocial

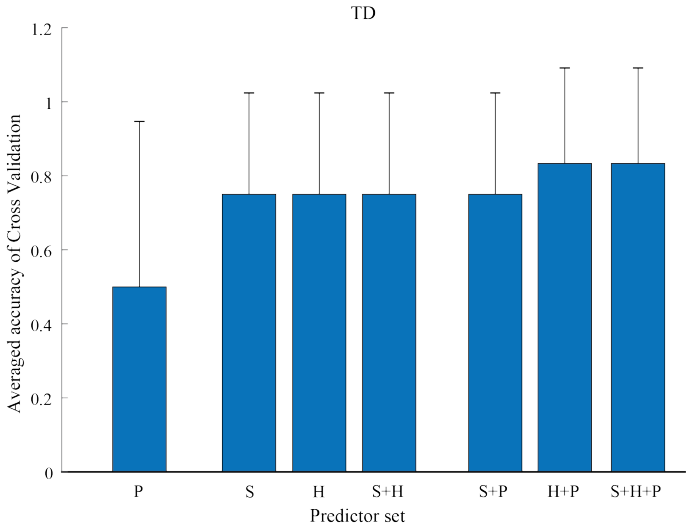

Figure 5.3 Accuracy of predicting prosocial behavior by three predictors.

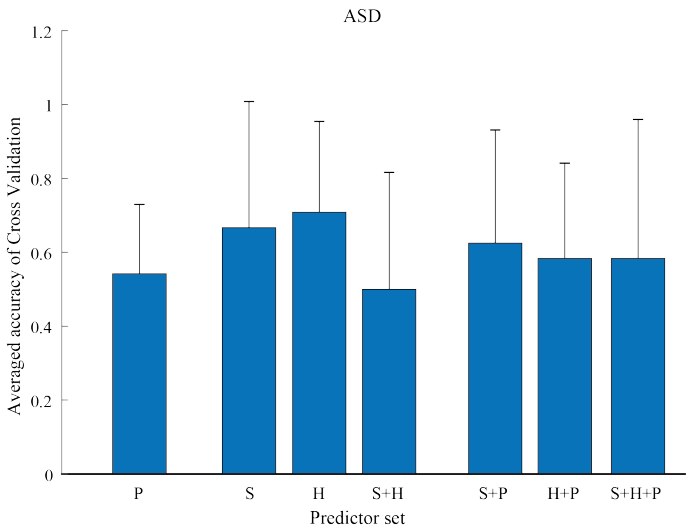

Figure 5.4 Accuracy of predicting prosocial behavior by three predictors.

behaviors were facilitated when prompting was provided after smiling or heading toward the robot. Also, 78% of prediction accuracy was achieved with only smiles or only heading toward the robot as predictors. This suggests that we could predict prosocial behavior of TD children with the single factor of smiling or heading.

On the other hand, for children with ASD, the highest accuracy of prediction was when heading toward the robot was used as a predictor. Prosocial behaviors could be predicted with 70% accuracy on average only with a heading. Smiling was the second most predictive variable. The prediction accuracy was 65%. With prompting, the prediction accuracy was low both when it was considered as a single factor and when it was combined with other factors. These results indicate that children with ASD showed more voluntary prosocial behaviors without prompting compared to TD children. Also, we could predict the prosocial behavior of children with ASD with the single factor of smiling or heading.

Although the prediction accuracy of heading is higher than smiling for children with ASD, detecting smiling can provide useful information for personalized robot-assisted therapy. In this study, all the children with ASD who smiled after watching the robot's movement showed prosocial behaviors voluntarily without prompting by the therapist or the parent. In contrast, all the children with ASD who did not smile after the robot's movement but showed prosocial behaviors received prompting by a therapist or a parent. This signifies that smiling might be a signal of voluntary prosocial behaviors. With this model, if smiling does not appear, we could predict the prosocial behaviors by detecting heading toward the robot. Therefore, it is possible for a therapist to control the robot to arouse smiles to facilitate voluntary prosocial behaviors. Also, a therapist can decide the timing of prompting to help children with ASD practice prosocial behaviors.

5.2.5 Conceptual Model

This study proposes a conceptual model based on the research results (Figure 5.5). We explored specific components of the framework. In robot-assisted therapy, we particularly observed smiles and a series of behaviors right after a robot's movement. Before engaging in prosocial behaviors, we observed smiling, heading, and approaching from each participant. The series of behaviors might be a social signal to notify the engagement in prosocial behaviors. Also, smiles might be the beginning of the signal. It indicates the potential of sensing the behaviors, decoding the social signal, and predicting the next engagement. The component of prediction in this model was investigated with a Bayesian model. With the prediction model,

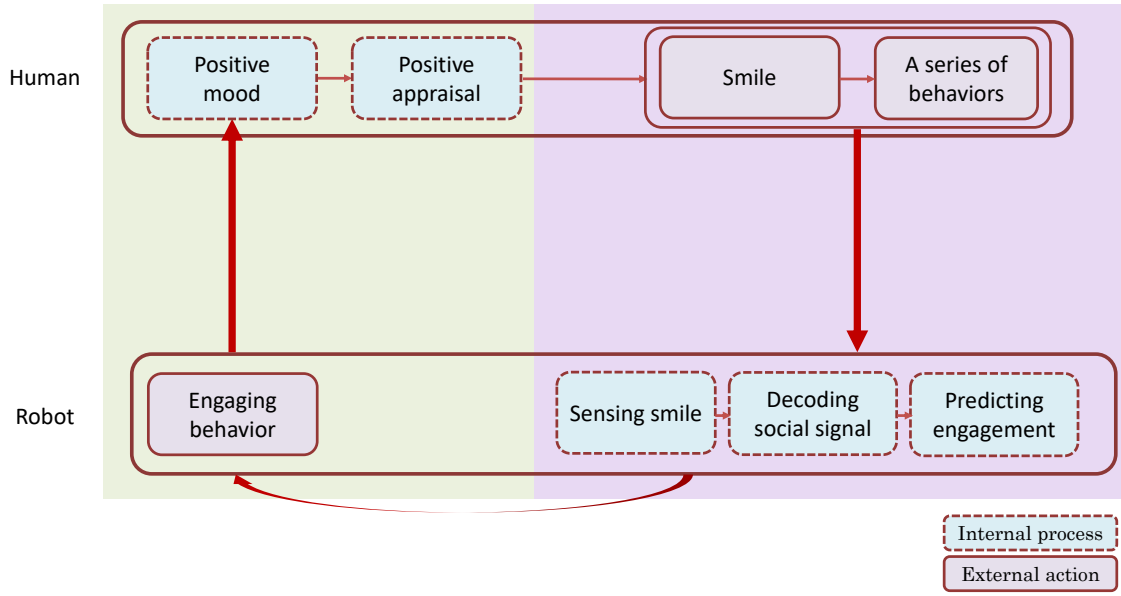

Figure 5.5 A proposed conceptual model.

the results indicate that we could anticipate the probability of prosocial behaviors by smile analysis. Therefore, this framework might be used for designing the next robot behaviors arousing positive mood to facilitate long-term engagement in healthcare settings.

5.3 Discussion

We explored possible behavioral factors, which can be a social signal of engaging in prosocial behaviors. Hypotheses were first, after a robot's movement, a series of behaviors of each child will be observed in robot-assisted therapy. Second, the series of behaviors will be represented by conditional probability in robot-assisted therapy. Third, the series of behaviors will predict the occurrence of prosocial behaviors toward a robot in robot-assisted therapy. To answer the research question and to verify the hypotheses, we observed possible behavioral factors before engaging in prosocial behaviors and represented the probabilistic relationships among the behavioral factors.

From the video analysis, we observed the four types of behaviors that might be connected in a time series. Smiles were followed by heading toward the robot, approaching the robot, and prosocial behaviors. In particular, voluntary prosocial

behaviors were observed when smiles appeared. Based on these findings, we proposed a probability model with a Bayesian network for predicting prosocial behaviors given smiles. As smiles were connected to a series of behaviors leading to prosocial behaviors, we considered smiles to be a possible signal to notify the intention of prosocial behaviors in the therapeutic setting.

However, the main limitation of this research is related to the generalizability of our results in other healthcare settings. The 36 cases from 6 TD children and 6 children with ASD are insufficient to generalize the model. To verify the hypothesis based on the proposed probabilistic model, single-case studies can be applied for the next study phase experiments. Even if the number of children who participate in the research is limited, multiple interventions per session will increase the number of cases for analysis.

Despite the limitations of this research, the results show that more prosocial behaviors toward the robot were observed when the smiles of a child were observed. This result highlights the potential benefits of smile analysis and the utilization of a robot to facilitate prosocial behaviors. Considering that smiles could be a signal of prosocial behaviors, personalized therapy for children with ASD could be possible by analyzing smiles, predicting prosocial behaviors, and arousing smiles. Therefore, if it is possible to predict prosocial behaviors consistently based on the proposed Bayesian model, this theoretical framework will enable future robot-assisted interventions to tailor a robot's behaviors according to smiles and other behaviors of each child with ASD. Moving forward from the previous studies that investigated the effects of robot-assisted therapy [20, 151], this research suggests how a robot's behaviors could be designed to facilitate engagement and how it could be applied to smile-related behaviors in robot-assisted therapy.

Chapter 6

Overall Discussion

In this study, two research questions were investigated.

- **RQ 1.** What kinds of behavioral planning of a robot are used to initiate engagement in healthcare settings?
- **H 1-1.** Combinations of human behaviors can be used as behavioral planning of a robot to initiate engagement in healthcare settings.
- **H 1-2.** Depending on situations, different behavioral planning of a robot will be preferred in healthcare settings.

The hypothesis was supported by survey-based experiments. The research question was to explore robot behaviors for initiating engagement in healthcare settings. We applied human behaviors to the behavioral planning of a robot. The results showed that different behavioral plannings were preferred to initiate engagement depending on situations. When joining a conversation of two people in a hospital, verbal behaviors after approaching were more preferred than nonverbal behaviors. When measuring temperature in a hospital, using a tool was more preferred than direct touch by a robot. It suggests that combinations of human behaviors can be used as behavioral planning of a robot to initiate engagement in healthcare settings as hypothesis 1-1. Also, different behavioral plannings of a robot were preferred in healthcare settings as hypothesis 1-2. Therefore, different combinations of behaviors can be used as behavioral planning of a robot to initiate engagement in healthcare settings. With the conceptual model, a robot behavior can be designed to initiate engagement by arousing positive mood and positive appraisal of humans.

- **RQ 2.** What kinds of behavioral factors affect the occurrence of prosocial behaviors toward a robot in robot-assisted therapy?

- **H 2-1.** There will be a positive relationship between human smiles and prosocial behaviors toward a robot in robot-assisted therapy.
- **H 2-2.** After a robot's movement, a series of behaviors of each child will be observed in robot-assisted therapy.
- **H 2-3.** The series of behaviors will be represented by conditional probability in robot-assisted therapy.
- **H 2-4.** The series of behaviors will predict the occurrence of prosocial behaviors toward a robot in robot-assisted therapy.

Due to the limited number of participants and therapy sessions, we were not able to verify the positive relationship between human smiles and prosocial behaviors toward a robot statistically. However, we observed a trend of positive relationships. The research question was to explore how to maintain engagement by recognizing social signals and predicting the next engagement. This question was investigated with the supposition that smiles might be the start of signaling engagement in prosocial behaviors. Although hypothesis 2-1 was not statistically verified, we observed a series of behaviors before engaging in prosocial behaviors as hypothesis 2-2. We observed that smiling, heading toward a robot, and approaching the robot subsequently happened before engaging in prosocial behaviors. Also, smiling, heading, and approaching were represented by conditional probability with a Bayesian model as hypothesis 2-3. Moreover, the series of behaviors could predict the occurrence of prosocial behaviors toward a robot in robot-assisted therapy as hypothesis 2-4. It indicates that the series of behaviors might be a social signal that we can predict the next prosocial behavior in therapy. It shows the potential of personalized therapy by predicting the next engagement and creating robot behaviors timely and appropriately in robot-assisted therapy.

By exploring two research questions, we proposed two models of robot behaviors. The conceptual model represents the initiation and maintenance of engagement. In the engagement process, we assume that a robot's behavior influences a human's affect, and the prediction of the next engagement adjusts robot behaviors cyclically. This model provides a holistic viewpoint for designing robot behaviors. Another model is for the prediction of engagement with a Bayesian approach. The Bayesian model describes behavioral factors, which can be a social signal, and the conditional probability of smiling and prosocial behavior. The proposed two models can be a framework to create adaptive robot behaviors to facilitate engagement.

6.1 Contribution to Human Informatics

This study was conducted to contribute to human informatics. Informatics is a discipline to solve problems by applying computing or computation [47]. Human Informatics is a discipline to solve problems in human-related domains by applying computing or computation. This study is to empower human healthcare service through the application of computing. Two directions of computing were applied in this study. One direction is to analyze human data by computing. To measure smiles as an indicator of positive mood and engagement, we recorded EMG from the facial muscles of participants in robot-assisted therapy and estimate smiles to complement unobservable video segments. The estimation was performed by signal processing with ICA and ANN algorithms. Another direction is to apply the findings to create a computational model. This study suggested a prediction model with a Bayesian approach. It is expected to improve the decision of designing robot behaviors in healthcare settings, and to improve the quality of healthcare service.

6.2 Potential Applications

The suggested models can be applied to a long-term interaction between a robot and a human in healthcare settings. The models provide a framework with changing contexts for designing robot behaviors. Particularly, the models include an interaction and engagement process. The interaction between a robot and a human can be started from the moment a person visits a healthcare environment. The models cover the process of designing robot behaviors to maintain engagement in specific therapy by recognizing and arousing human affect as well as to initiate engagement in general situations.

Also, these models could be applied to robot-assisted therapy for children with ASD in order to facilitate smile-related behaviors. By detecting relevant social signals, including smiles, from a child with ASD, the Bayesian model makes it possible to anticipate smile-related behaviors. Emotional empathetic behaviors and shared gaze behaviors might be related to smiles [28, 131, 137, 138], and they might be facilitated with these models. Based on the prediction, the behaviors of a robot are designed and created to arouse smiles from each child for facilitating a specific behavior. Moreover, a Bayesian approach can deal with the uncertainty and subjectivity of the observed phenomenon. As the variance of children with ASD is high, the proposed approach

with a Bayesian model is expected to apply for robot operation in personalized robot-assisted therapy for individuals with ASD.

Furthermore, these models have the potential to be extended for other training in healthcare settings. As it has been reported that positive affect and cognitive performance can be related [66, 109], the proposed models might be applied for cognitive training of elderly people. By arousing smiles timely with a robot, we might facilitate engagement in related activities, and improve the healthcare service.

6.3 Limitations

A conceptual model and a Bayesian model were suggested to design robot behaviors; however, there are limitations for applying these models directly to various healthcare settings.

6.3.1 Problem of Generalizability

Due to the limited number of participants and limited situations, the conditions of this study are insufficient to generalize the models. To initiate engagement, two situations in healthcare settings were selected and possible robot behaviors were investigated. However, the scenarios did not include other conditions of the hospital environment. Also, participants evaluated a robot's specific behaviors without other alternatives. To maintain engagement in robot-assisted therapy, only 6 children with ASD and 6 TD children participated in the activities. Moreover, the maximum sessions for this research included 2 sessions of children with ASD and 1 session of TD children. From the selected sessions, a total of 36 cases were analyzed for creating the Bayesian model. However, there is a possibility that different results will come out when more cases are collected.

The limitation of participants should be solved in future research. One way is to apply single-case studies. With this method, multiple interventions per session can increase the number of cases for analysis. Another possible method is to use the Monte Carlo technique. By simulating repeated random sampling, it can be possible to complement a limited number of cases and investigate causal relationships.

6.3.2 Compounding Variables

Due to the research design and methods, this study was not able to prove the causality between variables. For RQ 1, survey-based experiments using questionnaires were conducted. However, people might have different impressions of a robot when they listen to a robot's voice, watch a robot's behaviors, and interact with a robot physically. Also, the behavioral plannings of a robot might not be applied to other robots. For RQ 2, smiles and prosocial behaviors were investigated in robot-assisted therapy. As the research was not completely controlled and the number of participants was not enough, direct relationships between the two variables could not be verified statistically.

Moreover, not all connections between variables of the models were investigated. There might be more considerable variables between components or in each component of the conceptual model. To verify the variables and components in the models, long-term and extensive research are required.

Also, the effects of playing with the robot in robot-assisted therapy were not investigated. Future research should investigate how play affects mood or emotions towards a robot. Furthermore, it is possible that prosocial behaviors towards a robot influence the next smiles, and the smiles influence prosocial behaviors. These cyclic behaviors should be explored in future research.

Therefore, it is necessary to modify the proposed models more sophisticatedly based on future research results.

Chapter 7

Conclusions

Research Objectives. The objectives of this research were to propose models of robot behaviors to deal with the difficulties of designing robot behaviors in the diversity of interactions. This study suggested a conceptual model and a Bayesian model to design robot behaviors based on social signals for facilitating engagement. The conceptual model describes a possible process of creating robot behaviors in temporal and dynamic interactions. It represents the initiation and maintenance of engagement. The initiation of engagement was investigated by applying social signals to a robot in general situations of a hospital. The maintenance of engagement was investigated by sensing social signals from a human and predicting the next engagement in a specific situation of robot-assisted therapy. Regarding the process of prediction, the Bayesian model was proposed. It describes a way of predicting human engagement when the engagement is related to recognizable social signals including smiles. The two models provide a holistic viewpoint to design robot behaviors in healthcare settings.

Research Results. This study proposed models to design robot behaviors in healthcare settings. The components of the conceptual model were explored with two research questions. To explore how to initiate engagement, RQ 1 was investigated. This question was related to a robot's behavior and an appraisal of humans in the conceptual model. We conducted survey-based experiments to investigate humans' evaluation of robot behaviors. What kinds of behavioral planning of a robot are used to initiate engagement in healthcare settings? We found that combinations of human behaviors can be applied to the behavioral planning of a robot, and different behavioral plannings were preferred to initiate engagement in different situations. To explore how to maintain engagement, RQ 2 was investigated. This question was related to recognizing human social signals and predicting the next engagement in

the conceptual model. We analyzed video data to observe recognizable behaviors. What kinds of behavioral factors affect the occurrence of prosocial behaviors toward a robot in robot-assisted therapy? We observed that there are a series of behaviors which might affect the occurrence of prosocial behaviors towards a robot in therapy for children with ASD. The series of behaviors, which are smiling, heading, and approaching, might be a social signal to indicate the next engagement in prosocial behaviors. The prediction accuracy with the possible social signal in the Bayesian model was calculated by leave-one-out cross-validation, and smiling showed over 65% of accuracy to predict prosocial behaviors. Also, we applied electrophysiological measurement of a smile. We used a wearable device with EMG sensors and all participants did not report discomfort. The accuracy of the smile classification was 70 % on average, a maximum of 88% and a miniumum of 51%. The measurements of smiles made it possible to capture smiles that cannot be observed with the human eye.

Research Outcome. In this research, the conceptual model and probabilistic model provided a framework to design robot behaviors for creating long-term interactions with a human in healthcare settings. By considering the process and states of engagement, the models can be applied to design timely and appropriate robot behaviors. Particularly, affective and behavioral engagement were investigated in robot-assisted therapy. As smiles might be the first signal of engaging in a behavior, such as prosocial behaviors, the intervention with a robot could be possible based on smile recognition. If a robot can detect the smiles of each person and anticipate smile-related behaviors, it is expected to create personal robot-assisted therapy. In particular, this framework can be feasible by quantifying smiles with electrophysiological measurement. Thus, it can provide therapists with more resources to focus on sophisticated behavioral changes, and empower human healthcare service with a social robot.

Future Research. Three directions will be considered to deal with the limitations. The proposed models were based on a limited number of participants in limited situations. Also, unobserved or unexpected variables might be involved in the models. Therefore, we will first investigate the applicability and generalizability of the models in another therapy. With different participants and different social situations, the process of initiating engagement and maintaining engagement will be explored and adjusted. Second, we will investigate individualized healthcare services with the models. Not only finding common factors but also creating individualization in technology will be beneficial to each person who requires special

needs. Third, we will investigate the possible array of robot movements to trigger positive affect. With a more detailed set of robot behaviors, the effects of each robot behavior will be explored. Then, effective combinations of robot behaviors will be explored to convey social signals to humans. Lastly, other smile-related behaviors will be investigated to facilitate the behavior with these models. The possible behaviors related to smiles can be empathetic behaviors and shared gaze behaviors. We will explore if these behaviors can be facilitated during robot-assisted therapy for children with ASD in the next phase of research. If we observe a chain of behaviors between a smile and a targeted behavior consistently, these models may become a framework for designing robot behaviors in healthcare settings.

This research is a small step in changing society to be more inclusive. The biggest motivation of this study and future research is to minimize discrimination and giving everyone, including myself, experience to be accepted and embraced in society. Some people are isolated due to mental differences, physical differences, personal backgrounds, and so forth. How can we make all feel inclusive? I am approaching the question in two ways in my research. One way is to reduce the discriminable factors. It can be possible by education, learning, or training. Another way is to provide a personalized environment. It can be possible by finding the uniqueness of individuals as well as the commonality of humans. In both ways, machines can be a medium. The advantage of using machines is that it can change humans' lives dramatically when it is spread. Also, machines are a tool to find the uniqueness of each person. Particularly, robots are a good tool to simulate humans' minds and behaviors. At the same time, robots can be used to give a personalized experience. This study was conducted to explore a way of designing robot behaviors for inclusiveness.

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Publications

Journal Paper

- **SunKyoung Kim**, Masakazu Hirokawa, Soichiro Matsuda, Atsushi Funahashi, Kenji Suzuki. Smiles as a Signal of Prosocial Behaviors Toward the Robot in the Therapeutic Setting for Children with Autism Spectrum Disorder (Under review, 2nd round).
- **SunKyoung Kim**, Go Woon Kim, and Dahyun Kang. (2018) Users' Perception Based on Engagement Strategies of a Social Robot in a Conversation. Design Convergence Study, 17(5), 1-15.
- **SunKyoung Kim**, Sun-Kyoung Kim, Hye-Won Lee. (2015) The Effect of Hangul Print Size on Reading Speed of Young and Older Adults in a Computer Environment. The Korean Journal of Cognitive and Biological Psychology, 27(3), 367-384.
- **SunKyoung Kim**, Ko Eun Lee, Hye-Won Lee. (2013) The Effect of Hangul Font on Reading Speed in a Computer Environment. Journal of the Ergonomics Society of Korea, 32(5), 449-457.

Conference Paper

- **SunKyoung Kim**, Masakazu Hirokawa, Soichiro Matsuda, Atsushi Funahashi, Kenji Suzuki. (2018) Smiles of Children with ASD May Facilitate Helping Behaviors to the Robot. Proceedings of the annual meeting of the International Conference on Social Robotics (ICSR), Qingdao, China, 55-64.
- Dahyun Kang, **SunKyoung Kim**, Sonya S. Kwak. (2018) The Effects of the Physical Contact in the Functional Intimate Distance on User's Acceptance toward Robots. Companion of the annual ACM/IEEE International Conference on Human-Robot Interaction (HRI), Chicago, USA, 143-144.

Workshop

- Min-gyu Kim, Nahyun Lee, **SunKyoung Kim**, Sang-Seok, Yun. (2009) User Perception on IoT Based Social Robot Applications in Hospital Setting. Workshop of the annual ACM/IEEE International Conference on Human Robot Interaction (HRI), Daegu, Korea.
- Dahyun Kang, **SunKyoung Kim**, Sonya S. Kwak. (2018) Social Human-Robot Interaction Design Toolkit. Workshop of the annual ACM/IEEE International Conference on Human Robot Interaction (HRI), Chicago, USA.
- **SunKyoung Kim**, Dahyun Kang, Go Woon Kim, Sonya S. Kwak. (2017) Verbal and Nonverbal Greetings as a Unit of Social Interaction between Human and Robot. Workshop of the annual meeting of the International Conference on Social Robotics (ICSR), Tsukuba, Japan.