A Child and a Robot Getting Acquainted – Interaction Design for Eliciting Self-Disclosure*

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ABSTRACT
In order to facilitate a sustainable long-term interaction between a child and a robot they need to get acquainted with one another. In this paper we discuss the foundation, the rationale, and the evaluation (N = 75) of our design for an autonomous robot conversational partner that engages with Dutch children (8-11 y.o.) in a getting acquainted interaction. The main objective of the robot is to elicit children to self-disclose.

Firstly, we discuss five interaction design patterns (IDPs) that proved to be successful in autonomously eliciting and processing self-disclosures. Secondly, we compared two robot behavior profiles. The behavior profiles can be relatively considered as being more and less energetic. We manipulated the movement speed, the speech rate and volume, the use of high/low energy language, waiting time before responding, and the order of high/low energy activities. Results show that the less energetic behavior profile significantly leads to more self-disclosure.

KEYWORDS
Child-Robot Interaction; Social Robots; Interaction Design Patterns

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1 INTRODUCTION
We are designing a robot for pediatric oncology patients. The aim of the robot is to engage repeatedly and long-term with the children in such a way that they feel socially supported and experience less stress and anxiety. For this to succeed, a bond between child and robot needs to be formed [28].

In order for a bond to be formed, children need to get acquainted with the robot [7, 10, 25, 43]. People typically get acquainted by disclosing personal information to each other [1, 41]. Reciprocation is important for this process [17].

The more a child self-discloses, the more input the robot has to appropriately respond and adapt to the child. It will allow the robot to reciprocate with more targeted robot-disclosures [10, 35] and the robot can use the information to personalize and enrich future interactions as well, which is a necessary ability for sustaining a long-term interaction [26].

In this paper we focus on the *getting acquainted interaction*. Our goal is to design and evaluate an autonomous conversational robot that effectively elicits self-disclosure among children. To achieve that goal we designed five interaction design patterns (IDPs) [22] that facilitate an autonomous child-robot interaction. These IDPs deal with several challenges within the field [4]. For example, the poor performance of speech recognition for children [24] and the difficulty of natural language understanding [4].

Furthermore, we have designed a more and less 'energetic' robot in an attempt to cater to the specific needs of extraverted and introverted children respectively. The extraversion trait is one of the dominant factors that influences self-disclosure in human-human interaction [14]. Especially whether that trait matches between conversational partners [11].

We contribute by presenting a thorough analysis of the getting acquainted interaction (Section 2), an in-depth discussion of a novel collection of interaction design patterns and robot behaviors (Section 3), and a proper evaluation (75 Dutch children, 8-11 y.o.) of the design (Sections 4-7).

2 FOUNDATION OF DESIGN

We have based our design on how humans get acquainted with one another, how others have designed extraversion specific robot behaviors, and how this relates to autonomous child-robot interaction.

2.1 Getting Acquainted and Autonomous Child-Robot Interaction

The most natural way of getting to know someone is by striking up a conversation and talking about various topics freely [41]. Slowly you get to know each others' interests, preferences, and stance on certain topics [1]. This is called an unstructured dyadic interaction [19]. However, recognizing what children are saying in that kind of setting is extremely difficult [24], let alone understand what is said, store it in a meaningful way, and retrieve it for a future interaction [4].

The conversation therefore needs to be constrained somehow to keep it manageable for an autonomous robot. We have chosen for a format where the robot takes the initiative and asks questions. We call it the *structured dyadic interaction design*. It is a collection of interaction design patterns that facilitate an autonomous and structured conversation between a child and a robot. In Section 3.2 we discuss the design patterns in more detail.

2.2 Reciprocal Self-Disclosure

Getting acquainted is such a common occurrence between humans that we do not realize how complex that interaction really is. There are a lot of social protocols and biases at play [41]. Exchanging personal information about oneself is one of the most important mechanisms for getting acquainted [1]. This does not only apply to human-human relationships [12] but also to relationships between humans and artificial agents [10, 23, 25, 35].

One strategy for eliciting self-disclosure is by directly asking someone to self-disclose [45]. Important for keeping self-disclosure elicitation sustainable is reciprocation [17]. This means that the robot must be able to self-disclose as well [10, 35]. The more expressive the robot is the more self-disclosure is elicited [32]. If appropriately reciprocated the self-disclosures will become more intimate over time [17]. This suggests that we need to take appropriate care of the robot-disclosures while designing a getting acquainted interaction.

2.3 Robot Behavior Design for Extraversion

Not all people get acquainted in exactly the same way. Personality is an important factor that influences whether two individuals "hit it off" or feel "no connection" [41]. In particular whether their extraversion trait matches determines how much they self-disclose to each other [14]. We have chosen to design robot behaviors that can match the extraversion level of a child

Previous attempts of adapting robot behavior to the extraversion level of the child have gained mixed results [39]. For example, extraversion matching seems to be effective for motivating people to do exercises [42] or repetitive tasks [3]. However, in a quiz game with a robot advisor it did not matter if the extraversion level of the robot and the player matched [34].

Designing specific introvert and extravert robot behaviors is not trivial. For example, children could not distinguish between introvert and extravert robot behaviors in a mimicking game [38]. However, if participants perceive a difference in extraversion they prefer the robot that matches them [2].

3 DESIGN RATIONALE

In our situated Design Rationale we motivate and justify the design elements that we included in the design of our robot getting acquainted interaction [30].

3.1 Context and Scenario

The robot will ultimately be deployed in the hospital. To not strain the children too much [20, 29], we test our prototypes in a school setting first. As a consequence, the design must be generic enough to fit in both scenarios. We use the Nao robot (see Fig 2.) in our project, because we have a lot of experience with this platform and it offers a number of key features out-of-the-box (e.g. Dutch speech recognition).

The scenario of the getting acquainted interaction is structured as follows: first the robot introduces itself and its purpose. The robots demonstrates and practices with the children how they need to talk to the robot and press its buttons. To showcase the other capabilities of the robot two activities (a dance and a tickle game) are added, one before and the other after the getting acquainted conversation. The conversation is the main component. After the second activity the child and the robot say goodbye.

3.2 Structured Dyadic Interaction Design

The robot needs to facilitate a conversation between child and robot, where the robot autonomously elicits and process the child's self-disclosures. The most effective way to do this is by asking closed-ended questions that require one-word answers [21]. However, this would result in an interrogation rather than a getting acquainted conversation, possibly negatively impacting the willingness of children to self-disclose [45]. To deal with this problem we developed the structured dyadic interaction design. It is a collection of five related interaction design patterns (IDPs) that need to provide enough structure for the robot to effectively process self-disclosures, while being stimulating for self-disclosure elicitation.

3.2.1 IDP-1: Pairing closed-ended and open-ended questions.

Problem. When the robot only asks closed-ended questions to elicit self-disclosure it affects the kind of relationship the robot has with the child. It shifts towards a power relationship, rather than a friendship, where the child has less autonomy over what they can disclose. This not only limits the amount and intimacy of self-disclosure, but also inhibits friendship formation [15].

Principle. In an ideal situation the children can freely respond and even ask questions in return. Unfortunately, the technical limitations of speech recognition and natural-language understanding for children currently prevent this from being realized [4, 24]. However, it is possible to use speech activity detection to detect when children are talking. This opens up the possibility to ask open-ended questions, that the robot does not (need to) process, allowing children to freely respond. This would return some of the autonomy back the the children.

Solution. This design pattern introduces two types of questions, closed-ended and open-ended. Closed-ended questions require a specific valid answer and present those answers in the phrasing of the question. A valid answer is an answer that can be recognized and processed by the robot. A (set of) valid answer(s) always needs to be prespecified. Closed-ended questions are either "yes/no" or multiple choice questions. Open-ended questions have no valid answer, i.e. accept all answers. The robot will only wait for the child to finish answering and will not process the answer.

The closed-ended and open-ended questions always come in pairs. The robot first asks a closed-ended question. For example, "If you have to choose a favorite holiday destination, which country would you choose? France, England, or Switzerland?". Using the answer of the child, the robot asks a open-ended follow-up question. For example, "Why is France your favorite out of those three?". The closed-ended questions provide all the information the robot needs to personalize future interactions, while the open-ended questions allow the children to freely respond increasing their autonomy.

3.2.2 *IDP-2: Pseudo-open-ended questions.*

Problem. A pitfall of overly structured dialog scripts is that over time the pattern of interchanging closed-ended and open-ended questions might get dull, resulting in children losing interest.

Principle. Adding more variation to the interaction is one way to increase long-term engagement [26]. Specifically, adding another type of question that can process self-disclosures would be helpful. By carefully designing a question [8] and by knowing the interests of children it should be possible to accurately predict their answer. This opens-up the possibility to ask a pseudo-open-ended question.

Solution. A pseudo-open-ended question requires a valid answer but the possible answers are not included in the question. This might give the illusion that any answer is possible, increasing the autonomy of children [15]. However, by carefully choosing the topic, phrasing it to elicit a short a specific response, and if necessary do a pilot study, most possible answers should be predictable. For example, "What is your favorite pet?". The list of specific valid answers, e.g. 'dog', 'cat', needs to be provided in advance.

3.2.3 *IDP-3: Positive backchanneling.*

Problem. Self-disclosure elicitation is not only about asking questions, but also about responding appropriately to those disclosures [6].

Principle. At the bare minimum the robot must acknowledge a response by the child. Better yet, the robot responds to what is being said [6]. This is what backchanneling is for [37].

Solution. The robot uses three different backchannel responses: non-lexical, phrasal, and substantive [47]. A non-lexical backchannel is a vocalized sound aimed to show the child that the robot is actually listening. For example, "uhuh". A phrasal backchannel is a short verbal response to acknowledge the answer of the child. Explicit agreeing responses have been found to elicit more self-disclosure then more neutral responses [27]. For example, "That's my favorite too!". A substantive backchannel is aimed to elicit an extended answer by the child. For example, "Go on. Tell me more". This last one is especially suitable for open-ended questions.

3.2.4 *IDP-4: Touch-based recognition and repair pipeline.*

Problem. Speech interaction is an important aspect for child-robot bonding [5]. But given the overall poor performance of speech recognition for children [24], a robust repair mechanism needs to be in place.

Figure 1: Children can use the buttons on the Nao's feet to answer a question whenever speech recognition fails.

Principle. Instead of only relying on speech we can make use other input modalities of the robot [5]. We have chosen for a touch-based repair mechanism. On a side note, touch has been found to have a positive impact on self-disclosure elicitation by robots [40]

Solution. To not discourage talking to the robot we allow for two speech recognition attempts per question. If after two attempts no response was successfully recognized, the robot switches to the touch modality. We put a 'No' sticker on the left foot and a 'Yes' sticker on the right foot of the robot (see Fig 1.). On its feet the Nao has a 'bumper' that can be pressed. For "yes/no" questions the appropriate bumper can be pressed directly. For multiple choice and pseudo-open-ended questions the robot lists all the possible answers and instructs the child to press the yes-bumper when the robot calls out the right answer. Two touch attempts are allowed. In case that would fail, the robot moves on to the next question. Note that this pattern does not repair incorrectly recognized speech.

3.2.5 *IDP-5: Six-step turn-taking.*

Problem. A child-robot conversation is difficult for both child and robot at first. Instructions help the child. But even little misconceptions can complicate things. For example, even though given the opportunity to answer freely to open-ended questions, some children may still answer verbosely to closed-ended questions. The robot has trouble processing these answers.

Principle. By consistently and appropriately directing the turn-taking, children should quickly pick-up how to smoothly talk to the robot, while the robot is provided with a robust structure for asking various questions and providing appropriate responses.

Solution. A repeating six-step turn-taking mechanism. The steps: 1) the robot takes the initiative by starting off with a closed-ended or pseudo-open-ended question, 2) followed by an answer from the child, 3) which in turn causes the robot to respond. 4) The robot subsequently asks the child to explain their answer, 5) followed by a response by the child, 6) that the robot acknowledges with a response. A response by the robot can either be a backchannel or a reciprocal self-disclosure by the robot (see next section). This pattern builds on pattern IDP-1 to 4.

3.2.6 *Robot Repertoire.* Not only the structure of the conversation, but also its content is important for getting acquainted and eliciting self-disclosure. We use the term *robot repertoire* to describe the collection of questions, backchannel responses, and robot-disclosures the robot can share.

The questions are mostly about identifying the favorite item for a particular topic. For example, the favorite pet or favorite season. The topics included in our implementation are sports, leisure activities, books, pets, seasons, colors, holidays, and television. These topics are selected because they aim to directly elicit self-disclosures of an appropriate intimacy level for a getting acquainted interaction [1]. Moreover, children are used to these kind of questions. For example, they are often included in friendship books.

The robot can respond in two different ways. It either gives a backchannel response or it reciprocates the child's self-disclosure by giving a robot-disclosure. Robot-disclosure is important due to the reciprocal nature of self-disclosure [7, 10]. Robot-disclosures are fictional anecdotes of the robot's personal life. Children are generally aware that these anecdotes are fake, but have the tendency to play along for the sake of the story [4].

The following example, of an actual conversation between child (C) and robot (R), shows the structured dyadic interaction design patterns instantiated with robot repertoire elements.

> R: "What is your favorite pet?" [pseudo-open-question]
> C: "A dog.' [recognized by speech recognition]
> R: "Oh nice, why is a dog your favorite pet?" [open-ended-question]
> C: "Because they are very playful." [speech activity detection]
> R: "Go on. Tell me more." [substantive backchannel]
> C: "We have a Golden Retriever at home."
> R: "I know a dog called Buddy. Buddy really likes to play fetch. One time he even jumped in the river to get his ball back." [robot-disclosure]

3.3 Extraversion Adaption

To further increase our efforts to elicit self-disclosure we have designed two behavior profiles for the robot. One profile is specifically designed for extraverted children and the other for introverted children. We looked at a wide range of typical marker differences for introvert and extravert human behavior. We translated these behavior differences to a number of behavior settings for the robot (see Table 1).

Extraverts have a more energetic behavioral profile than introverts. For example, extraverts talk more, faster, louder, use fewer pauses, and less formal language, produce responses with shorter latency, use more positive emotion words, and agree and compliment more [31]. To create matching robot behaviors we designed a more energetic robot for extraverts and a less energetic robot for introverts. The less energetic robot talks slower and softer compared to the more energetic robot. It also waits longer for a response by the children.

The less energetic robot uses more tentative words and uses less social and weaker positive emotion words. For example, "Cool. Could you tell me more?". The language of the more energetic robot, on the other hand, is more directive (i.e. less tentative words) and contains more social and stronger positive emotions words. For example, "That is an awesome choice! Tell me more.".

Furthermore, as in [2, 13], we have also varied the amplitude and speed of the movements. We varied the arms, head, and torso

Table 1: Behavior settings for less and more

Behavior Setting	More energetic	Less energetic
Speech speed	100%	90%
Speech volume	49	40.5
Language style	directive	interrogative
Emotion words	strong	weak
Speech activity detection interval	2-3s (100%)	2.5-3.75s (125%)
Gestures amplitude	100%	60%
Gestures speed	100%	50%
Head movement speed	100%	75%
Breathing animation	20 bpm	10 bpm
Activity order	Dance - game	Game - dance

separately. The arms display random gestures when the robot is talking. While keeping the frequency of the gestures the same they are slower and smaller for the less energetic robot. The robot nods its head while listening. The head movements of the less energetic robot are slower, reducing the frequency. Finally, the torso moves slowly from left to right to simulate breathing. The less energetic robot has less 'breaths' per minute (bpm).

A final element we manipulated is the order of two activities (dance and tickle game) in the getting acquainted interaction (see scenario description in section 3.1). These activities cannot be seen separately from the 'energeticness' of the robot and could influence the elicitation of self-disclosure. The dance is far more energetic than the tickle game. Therefore, the less energetic robot has the tickle game before the conversation and the dance after. For the more energetic robot it is the reverse.

The exact settings as listed in Table 1 were established via rapid prototyping and small pilots with children and adults. The settings are meant to create enough contrast between both behavior profiles to match with introverted and extraverted children, while still resulting in a decent conversational partner. For example, if the robot would talk too slow or too fast children would not be able to understand the robot anymore.

4 RESEARCH QUESTIONS AND HYPOTHESES

For our evaluation we have two goals. First we want to evaluate the structured dyadic interaction design and secondly we want to measure the effects of the energetic behavior on self-disclosure for introverted and extraverted children. The first research question (RQ1) is: *how effective are the five interaction design patterns for maintaining an autonomous getting acquainted conversation?* The following sub-questions evaluate the effectiveness of each pattern.

(1) How successful are the different questions in eliciting self-disclosure? Indicated by the response rates of the three types (closed-ended, pseudo-open-ended, and open-ended) of questions. *[IDP-1, 2]*
(2) Do children give valid (i.e. predicted) answers to the pseudo-open-ended and closed-ended questions? *[IDP-2, 1]*

(3) How successful are the backchannels for eliciting self-disclosure? Indicated by the response rates to the three types (non-lexical, phrasal, and substantive) of backchannels. *[IDP-3]*
(4) How successful is the recognition and repair pipeline and is the touch-based mechanism an effective alternative? Indicated by the recognition performance. *[IDP-4]*
(5) How often is speech incorrectly recognized and how do children respond to those mistakes? Due to the lack of a repair mechanism for incorrectly recognized speech it is important to assess the impact of those mistakes. *[IDP-4]*
(6) How successful is the six-step turn-taking mechanism? Success means that children give a concise answer to the initial closed-ended/pseudo-open-ended question and leave a verbose answer for the follow-up open-ended question. *[IDP-5]*

The second research question (RQ2) is: *What effect has the energeticness of the robot on self-disclosure for introverted and extraverted children respectively?* Following our design we have formulated the following hypotheses: the extraversion of participants and the energeticness of the robot interact such that extraverts self-disclose more (H1a) and more intimate (H2a) to a more energetic robot and that introverts self-disclose more (H1b) and more intimate (H2b) to a less energetic robot. We furthermore expect that, just like within human-human dyads [14], extraverts are more willing to self-disclose (H3).

5 METHOD

5.1 Experiment design

We used an 2x2 between-subject study design for RQ2. The two independent variables are the extraversion of the child (introvert versus extrovert) and the behavior adaptation of the robot (more or less energetic). The two dependent variables are the amount and the intimacy of self-disclosure. The interaction design patterns were implemented across all conditions. All the interactions that were included in the experiment were used to evaluate the IDPs (RQ1).

5.2 Participants

75 children, between 8 and 11 years old, of two Dutch primary schools (school A and B) completed the experiment. 45 girls and 30 boys were recruited from two classes per school. In school A and B respectively 41 and 34 children participated.

The age, sex, and extraversion level of participants were kept balanced while assigning participants to a condition. Per school participants with the same sex, age, and extraversion level were randomly paired. Randomly one was assigned to the matching robot and the other to the mismatching robot.

5.3 Materials and set-up

A standard Nao robot was used with its default speech recognition software. A Sony HDR-handycam was used to record the interaction on video and audio. All robot commands were executed on the robot by the default Naoqi framework. All custom-made software ran locally on a standard issue Dell laptop.

The experiment took place in two rooms both familiar to the participants. The first, the interaction room, was a spacious room

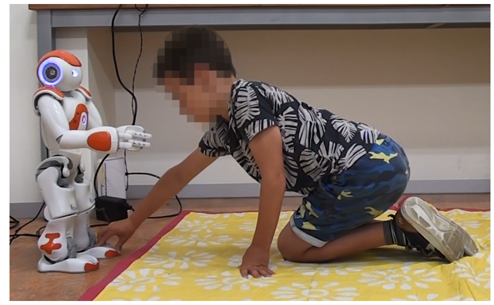

Figure 2: Child pressing one of the answer bumpers on the Nao Robot. The image is a screen shot from the camera.

(an arts and crafts room in school A and a surplus classroom in school B) where the participants interacted with the robot. The second, the interview room, was a small workroom mostly used, in both schools, for homework guidance or quiet working.

During the interaction the participants were asked to sit in front of the robot on the floor. The experimenter in the room was seated out of view. The camera was placed on a small stool, to make it blend in without completely obscuring it, perpendicular to the child and robot (see Fig 2).

5.4 Procedure

The experiment was approved by the ethics review board of the Delft University of Technology. All teachers, parents, and the children received an information booklet about the experiment and signed a consent form before participating. The experiment was run for several days spread over a two week period. A week before the start teachers filled in extraversion questionnaires for each participant. On the first day the Nao robot was shown, in an idle state, to all participating class rooms. The global procedure was explained and children could ask questions.

Children were collected from the class room one after the other and escorted to the interaction room. Upon entry the robot was hidden from sight. The participants were explained that they would have a conversation with the robot and that afterwards they would be asked to tell us what they thought about it. Furthermore, it was pointed out that they could stop at anytime without consequences or giving a reason.

When the participant was ready the robot was revealed and placed in a squatting position on the ground. The participants were asked to sit in front of the robot on the ground. The experimenter briefly demonstrated where the buttons on the robot were, how to press them, and emphasized that they should talk loudly and clearly to the robot. Then the robot and the camera were turned on. A detailed description of the interaction design is given in section 3. The interaction lasted for approximately 15 minutes.

After the interaction was over the participants were escorted to the interview room where they were interviewed. Finally, the participants were thanked and asked to not discuss the experiment with their peers until the experiment was finished.

5.5 Measures and instruments

5.5.1 Interaction Design Pattern Evaluation. All conversations between participant and robot were transcribed to text. Using the transcriptions we determined for each question (RQ1-1) and backchannel (RQ1-3) attempt whether it elicited a response by the participant and whether it was valid (RQ1-2). We calculated for each question the average amount of characters and whether it was too verbose (RQ1-6).

We logged each speech recognition and, in case of a failure, repair attempt. This allowed us to calculate the success rate of each step in the recognition and repair pipeline (RQ1-4). We also logged every time the speech recognition recognized an answer incorrectly together with the response to that error by the participant (RQ1-5).

5.5.2 Self-disclosure. The notion of self-disclosure is a multi-layered concept. We measured two different aspects: the AMOUNT and the INTIMACY of self-disclosure. Two annotators used a set of instructions to annotate the responses. Annotator disagreements were resolved in a discussion after completing the annotations.

The AMOUNT of self-disclosure is operationalized as the total count of unique statements related to oneself within all the responses made by a participant. The annotators marked and counted the unique statements per response. Summing these statements resulted in the total amount of self-disclosure per participant. To summarize the instruction set, every part of the response that is or could syntactically be separated by either a comma or an ‘and’ should be counted as a unique statement. For example, “I always wanted to have a cat" counts as one and “I like to play football and tennis” counts as two. An exception however is when two parts of a statement belong to the same concept. For example, “My favorite TV-show is Tom & Jerry” counts as one.

The INTIMACY measure of each self-disclosure is based on the Disclosure Intimacy Rating Scale for child-agent interaction. The scale contains four increasing levels of intimacy that are based on the risk of receiving negative appraisal and the perceived impact of betrayal by the listener [9]. Their research shows that almost all self-disclosures of an initial interaction fall under the first level.

To increase the expressive power of the disclosure intimacy rating scale we designed a level 1 subscale specific to the type of interaction present in our experiment. Using 20 randomly selected statements 5 sublevels were defined. To indicate a relative difference between the levels, a score between 0 and 3 was attached. The levels are related to the type of argumentation given by the participants to justify an answer. In table 2 the levels are illustrated based on responses to the question “Why is France your favorite holiday destination?”.

The total INTIMACY score is the summed intimacy scores of each response (not statement). Children can for example have a high amount of self-disclosure but a low intimacy score and vice versa.

5.5.3 Participant and Robot Extraversion. To categorize participants either as introvert or extravert we used the extraversion subscale of the Hierarchical Personality Inventory for Children (HiPIC) [33]. Teachers rated for each participants the 32 items from the extraversion subscale. We used a mean split, per classroom, to label participants as introverts or extraverts. We selected 8 suitable items from the HiPIC questionnaire and asked the participants to rate the extraversion level of the robot.

Table 2: Example of self-disclosed statements with an intimacy level and score assigned

Level	Self-disclosure	Score
No argument	“Because it is my favorite.”	1
Fact	“Because Disneyland is there.”	2
Personal fact	“Because my aunt lives there.”	3
Opinion	“Because it’s the most beautiful country in the world.”	3
Other	“I don’t know” or “What is yours?”	0

Table 3: Question response rates and lengths

Type	#	Res. rate	Valid	Avg. Chars.
Closed-ended	542	98%	97%	9±7
Psuedo-open-ended	285	99%	95%	12±10
Open-ended	533	88%	n/a	40±32

Table 4: Backchannel response rates

Type	#	Res. rate
Non-lexical	117	21%
Phrasal	74	51%
Substantive	190	85%

6 RESULTS

6.1 Autonomous Structured Dyadic Interaction

To answer the research question RQ1-1 and RQ1-2 we present the rates of the total and the valid responses to all the questions asked by the robot in Table 3. To answer research question RQ1-3 we present the response rates to all backchannel attempts in Table 4.

We evaluated two aspects of the performance of the touch-based recognition and repair pipeline (IDP-4). First we looked at the ability to recognize a valid answer (RQ1-4). In Fig 3. a funnel overview is presented that depicts the success/failure ratio for all four steps of recognizing a valid answer. The second aspect is the effect of incorrectly recognizing an answer (RQ1-5). Of 812 attempts the robot recognized an answer 71 times (8.7%) incorrectly. The different ways participants responded to these recognition errors are displayed in Fig 4.

To answer the reseach question RQ1-6 we looked at the average character count for the answers to questions (see final column of Table 3). Of the 812 times a participant responded to a closed-ended and pseudo-open-ended question 28 times (3.5%) they responded too verbosely, resulting in a speech recognition failure.

6.2 Robot’s Energeticness, Participants Extraversion and Self-Disclosure

A two-way MANOVA was run with two independent variables – participant’s extraversion and the robot’s energeticness – and two

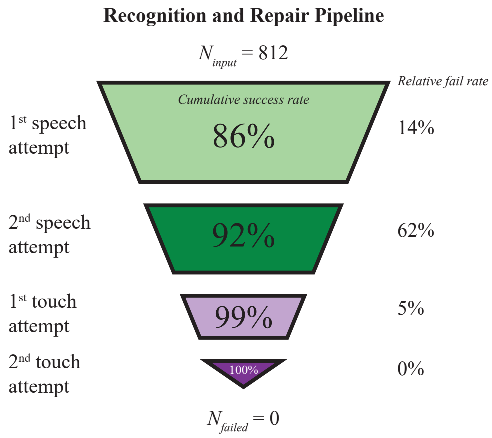

Figure 3: Success rates of the recognition and repair pipeline.

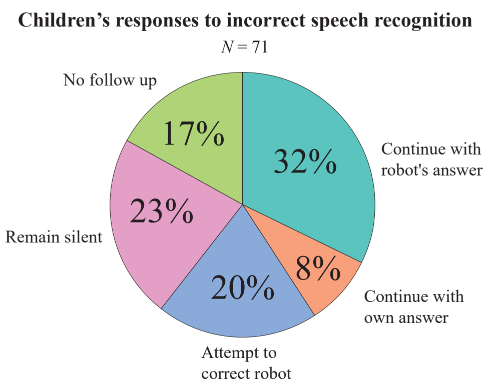

Figure 4: Pie chart representing the participant's responses to a follow-up question after their initial answer was incorrectly recognized.

dependent variables – the amount and intimacy of self-disclosure (see Fig. 5 and 6). The interaction effect between extraversion and energeticness was not statistically significant, $F(2, 69) = .012, p = .988$, *Pillai's Trace* $V < .001$, $\eta^2 < .001$. There was a statistically significant main effect of the energeticness on self-disclosure, $F(2, 69) = 3.501, p = .036$, *Pillai's Trace* $V = .092$ $\eta^2 = .092$. There also was a statistically main effect of extraversion on self-disclosure, $F(2, 69) = 6.329, p = .003$, *Pillai's Trace* $V = .155$, $\eta^2 = .155$.

Follow up univariate two-way ANOVAs were run considering the main effect of the robot's energeticness. There was a statistically significant main effect of the energeticness on the AMOUNT, $F(1, 70) = 6.064, p = .016$, $\eta^2 = .080$, and the INTIMACY of self-disclosure, $F(1, 70) = 6.396, p = .014$, $\eta^2 = .084$. Participant disclosed more to a less energetic robot, 27.25 ± 1.50, than to a more energetic robot, 21.95 ± 1.54. Moreover, the self-disclosures were also more intimate when disclosed to a less energetic robot, 29.14 ± 1.00 versus 25.50 ± 1.02.

Follow up univariate two-way ANOVAs were run considering the main effect of extraversion. There was a statistically significant main effect of extraversion on the AMOUNT, $F(1, 70) = 10.413, p = .002$, $\eta^2 = .129$, and the INTIMACY of self-disclosure, $F(1, 70) = 11.969, p = .001$, $\eta^2 = .146$. Extraverts disclosed more (28.07 ± 1.52) and more intimate (29.804 ± 1.02) than introverts (21.13 ± 1.52 and 24.84 ± 1.01).

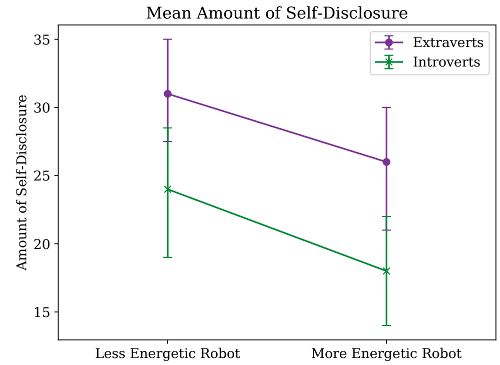

Figure 5: Mean amounts of self-disclosure for energeticness and extraversion with 95% confidence intervals.

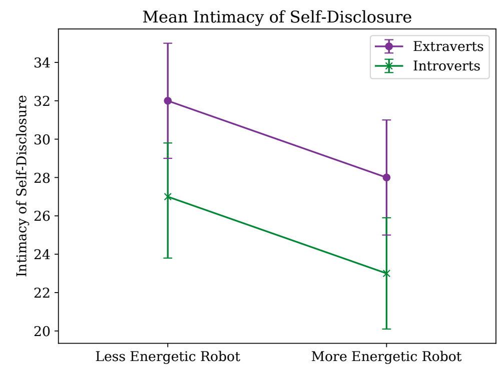

Figure 6: Mean intimacy scores of self-disclosure for energeticness and extraversion with 95% confidence intervals.

To check whether the participants perceived the extraversion of the robot as differently an independent-samples t-test was run. Participants rated the extraversion level of the less energetic ($4.03 \pm .43$) not significantly differently than the more energetic robot ($3.97 \pm .36$), $t(73) = .649, p = .518$.

7 DISCUSSION

We have evaluated different aspects of the effectiveness of the five structured dyadic interaction design patterns (IDPs). The high response rates to the closed-ended (98%) and pseudo-open-ended questions (99%) show that the robot can use it to effectively elicit self-disclosure. The high response rate of the open-ended questions (88%) confirms that most children want to (and do) freely explain themselves. This validates the pairing closed-ended and open-ended questions pattern (IDP-1).

Although pseudo-open-ended questions (IDP-2) seemed unrestricted only in 5% of the cases an invalid (unspecified) answer was given. In most of those 5%-cases the robot did not recognize an answer and children ended-up choosing a different, but valid, answer via the touch-repair mechanism. This shows that with the right questions and preparation less restricted questions can be asked, validating IDP-2. The questions can be improved by including the unspecified answers in the next iteration. This needs to be done carefully because too many answers decreases the overall recognition rate.

The backchannel (IDP-3) response rates show that substantive backchannels are the most effective (85%). Phrasal (51%) and non-lexical (21%) backchannels underperform. We believe it is mainly due to insufficient timing. The video footage suggests that participants often thought the non-lexical or phrasal backchannels were the start of the next question and they simply waited until the robot continued.

The success rate of the touch-based recognition and repair pipeline (IDP-4) shows that it is highly effective (100%) in processing valid responses. If speech recognition fails the first time it fails for 62% the second time. This indicates that switching to the touch modality is a necessary approach. 93% of the first touch recognition attempts succeed, validating IDP-4.

In 8.7% of the time an answer was incorrectly recognized. The most common response was that children adopted the incorrect answer as their own for follow-up questions. This confirms that children are receptive to influences by the robot [44]. It is highly desirable to implement a repair mechanism for these type of errors, otherwise the robot might personalize a future interaction based on incorrect information.

The results of the six-step turn-taking pattern (IDP-5) show that in 96.5% of the cases a child responds concisely when they need to. This is confirmed by the average character count that furthermore shows that children, as intended, significantly elaborate more during the open-ended follow-up questions. IPD-5 makes it easy to understand for children how to talk to the robot, validating IDP-5.

We have furthermore evaluated the behavior manipulations that were designed to elicit self-disclosures from introverted and extraverted children with a 2x2 between-subject user study. The results show no significant interaction effect of extraversion and the energeticness of the robot on self-disclosure. Instead, the results show that both extraverted and introverted children self-disclosed more and more intimately to the less energetic robot. We can therefore accept hypotheses H1b and H2b, but need to reject hypotheses H1a and H2a.

Results furthermore confirmed hypothesis H3 by showing that extraverted children significantly self-disclose more and more intimately than introverts. The known tendency of extraverted children to be more willing to self-disclose [14] also holds for child-robot interaction.

Children did not rate the extraversion level of both robots as significantly different. One explanation is that the measurement was biased by the highly energetic dance activity. It was present in both robots, only the order (before or after the conversation) was different. Although the order difference made sure an extraversion matching effect could still occur, it is not likely that it did, because then we would have found the expected interaction effect. As a result, we conclude that the less and more energetic robot cannot be considered as being distinctly introvert and extravert and that no extraversion matching effect occurred.

An important lesson we take away from this is that it is difficult 1) to define what constitutes intro/extravert behavior for a robot, 2) to design concrete robot behaviors that are distinctly perceived as intro/extravert, and 3) to measure the perception of children regarding the extraversion of the robot and whether it matches. The question arises of whether we really need to create an intro/extravert robot to optimally facilitate self-disclosure, getting acquainted, or perform any other function? Especially since we are not the only ones having trouble [39].

The video footage revealed a number of leads why the less energetic robot is more effective. It seems to be more 'in sync' with the children. In sync means that the timing of, for example, the gestures, the questions, backchannels, and turn-taking is contingent with the speaking behaviors of the children. This is a defining feature for creating rapport [18]. More rapport leads to more self-disclose [16, 48]. It also might be the case that the less energetic robot creates a more relaxed setting for the conversation. Good interviewers, especially in uncomfortable scenarios, create a relaxed setting explicitly and implicitly to elicit more self-disclosure [36, 46].

Finally, the limitations of this study lie in the assessment of the extraversion level of the robot, and the scoring of self-disclosure, in combination with the medium sample size for the complex study design. The extraversion scoring of the robot and the self-disclosure measures are not independently validated. Furthermore, the interaction design patterns are only jointly evaluated in this specific context. Our study would benefit from additional and independent validation and a larger sample size.

8 CONCLUSION

We evaluated a robot that autonomously engaged with children in a getting acquainted interaction. We designed five structured dyadic interaction design patterns. Results show that the design patterns allow the robot to effectively elicit and process children's self-disclosures by asking a combination of closed-ended, open-ended, and pseudo-open-ended questions. If speech recognition fails, the touch modality proved to be an effective back-up. Due to the six-step turn taking pattern children quickly pick up on how to effectively talk to the robot. Results show that improvements can be made by refining the timing of backchannels and adding a repair mechanism for incorrectly recognized speech.

We compared and evaluated a less and more energetic robot. Results show that the less energetic robot elicits more self-disclosure. Initially, we designed the two behaviors profiles to stimulate self-disclosure elicitation for introverts and extraverts. This was based on the concept of extraversion matching. However, the children did not rate the extraversion level of both robots as being different. We found that translating a high-level psychological construct, such as extraversion, to concrete robot behavior in a specific context is a difficult design challenge. We argue that focusing on concrete lower-level concepts, e.g. rapport, is a more effective approach.

We have taken the first steps in creating a robot that can autonomously interact repeatedly and long-term with children at the pediatric oncology department. The robot is now able to get acquainted with the child. The next step is to refine and expand our design such that the robot can use the things it learned about a child to personalize and enrich their future interactions.

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