Designing Social Dialogue Model for Human-Robot Interactions*

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Abstract— **Social interactions between humans and robots increase in diverse contexts. The overall purpose of the study is to build the social dialogue model by examining the detailed structure and elements of conversation between humans and robots. To design the social dialogue model, we collected conversation data using our own developed system. We recruited 80 participants who were randomly assigned to complete conversations through the system. After collecting the conversation data, we are currently in the process of tagging them with social cues such as self-disclosure, self-disclosure elicitation, acknowledgement, shared experience, and topic management. With the tagged data, we will build the social dialogue model with a series of social cues. The implemented social dialogue model could be applied to diverse conversational agents such as chatbots.**

I. Introduction

As the interactions between humans and robots increase, the need for social dialogue has also increased rather than simple fact-oriented dialogue [1]. To have more reliable social human-robot interactions, implementing the natural conversation of agents is crucial. To implement the natural dialogue of the agents, understanding and analyzing the structure of the social dialogue is needed.

To design the social dialogue model, we collected dialogue data with previously developed system in the lab (Figure 1) [2]. To collect social dialogue data, we distributed the designed Google survey forms to 80 different participants and gathered social dialogues. Currently, we are preparing a plan to analyze and tag the data with several social cues. After all the dialogue being tagged, we are going to construct a dialogue model that could reflect various social behaviors of humans during text-based chatting.

II. Literature Review

A. *Conversations between Humans and Agents*

People interact with diverse agents such as chatbots, social robots, smart speakers, and embodied conversational agents. The artificial intelligent agents perform diverse functions. They deliver the factual information to people [3].

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Figure 1 Overall procedure of the study.

For instance, agents report the weather condition, recommend the restaurants near the town, and give directions [4]. Meanwhile, agents could play a role as a conversational partner and have a small talk with people. To perform such functions well, social aspects of interactions between agents and humans are important [1].

B. *Contexts of Social Dialogue*

Social interactions between humans and robots are conducted in diverse contexts. A large number of previous studies were conducted in the context of educational settings such as peer-tutoring and classroom to analyze the social dialogue [5], [6], [7], [8].

In the context of peer-tutoring [8], dyadic computational model of rapport management was built for Human-Virtual Agent Interaction. Similarly, another social dialogue research was conducted in the context of peer-tutoring [7]. Social dialogue was analyzed with conversational strategies such as self-disclosure, referring to shared experience, and praise. In the context of classroom, conversation data were examined with the standards of culture and ethnicity, which examined the differences of verbal and nonverbal behaviors between African American and American virtual peers [9].

Several studies about social dialogue were conducted in the context of counseling. In these studies, the conversational agents played the roles as the professional experts in fields such as real estate [10] and museum [11]. Social dialogue between humans and REA (Real Estate Agent) was examined in the context of housing real estate [12]. Another study examined the message delivery of chatbots in the context of health counseling [13]. The study questioned whether the chatbots should provide informational support or emotional empathy when counseling the personal health problems [13].

C. *Analysis of Social Dialogue*

In previous studies, social conversations and interactions were analyzed with diverse standards that were adopted from previous studies. Researchers came up with their own set of standards and rules that match with the purpose of their research to analyze the conversation data. In average, three to four coders annotated the data to increase the inter-coder reliability [14].

To build the automatic recognition of conversational strategies in the service of a socially-aware dialog system, previous study applied the conversational strategies such as self-disclosure, referring to shared experience, praise, and violation of social norms [8]. To investigate the different social functions of language in teen peer-tutoring dialogues, the standard of politeness such as message enforcers, politeness, and laughter were used to annotate the dialogue [15]. Similarly, Brennan et al. also applied the concept of politeness to analyze the electronic conversations, but the hedge was the main standard of annotation [16].

To analyze the cultural differences between African American students and American students in social dialogue, phonological features of African American English (AAE) were applied [9], [17]. In another study comparing the women's and men's speech, hedges were applied to analyze the conversations [18].

III. METHOD

A. Data Acquisition

We used a dialogue data acquisition system that automatically acquires dialogue data from multiple users through Google form [2]. A total of 80 participants were recruited from the college community website to collect dialogue data. The participants were aged from 20 to 30 years old.

B. Analyzing the Data

We are currently in the process of tagging the collected conversation data. To minimize the inter-coder variability, a total of six coders are recruited and tag the conversation data [9]. To make sure that all coders have shared understandings of explicit standards and definitions of social cues, we conducted the guide session in advance, where specific examples of utterances for each social cue would be given to coders along with the definitions of each cue. Each social cue was selected based on previous studies: self-disclosure elicitation, self-disclosure, acknowledgement, shared experience, praise, topic maintenance, topic deviation, topic shift, and non-verbal act (Table I).

Self-disclosure and self-disclosure elicitation cues help build the rapport between conversational partners. Self-disclosure refers to the expressions to reveal aspects of themselves to others [7]. It often occurs when people reveal their personal private information, emotional disclosure, and personal opinions. Through self-disclosure, conversational partners could build rapport and intimacy [12]. In addition, self-disclosure in the conversation could make the person to be perceived as more intimate and attractive [19]. Self-disclosure elicitation refers to the social cue that elicits the conversational partners to self-disclose themselves [20].

In the self-disclosure elicitation cue refers to the utterances and questions that elicit the thoughts and feelings of the conversational partner. Self-disclosure elicitation cue leads one's interlocutors to provide information about themselves [8]. Self-disclosure refers to the disclosure of emotions and inner thoughts. Past experience cue refers to disclosing and sharing one's past experiences.

TABLE I. THE LIST OF SOCIAL CUES USED TO ANALYZE THE CONVERSATION

Social Cues	Definitions
Greetings	Start of the conversation
Self-disclosure elicitation	Leading one's interlocutors to provide information about themselves.
Self-disclosure	Revealing personal and private information about themselves.
Suggestion	An idea or plan to put forward for consideration.
General statement	Information or experiences heard from others.
Simple yes/no answer	Simple answers ("yes", "no") for questions
Acknowledgement	Harmony or accordance in opinion or feelings, a position or results of agreeing
Praise	The expression of a favorable judgement of an attribute, behavior or product of other person.
Termination	End of the conversation

Suggestion cue refers to putting forward a plan or idea for someone to think about [7]. General statement refers to the information or experiences heard from others. Simple yes/no answer cue refers to the simple "yes, no" answers for questions.

Acknowledgement indicates that conversational partners have demonstrated the empathy with each other. Acknowledgement refers to the signal of understanding by acknowledging the information delivered by the conversational partner was understood and accepted [21]. Acknowledgements are usually expressed explicitly with non-verbal behaviors such as eye gaze and head nodding [22]. Meanwhile, we adopted the cue of acknowledgement as verbal act in this study. Praise refers to positive interpersonal feedback that increases task-related behaviors, motivations, and feelings [23]. Studies in human-computer interaction have shown that by offering praise with words, computer can lead users to be more open to persuasion [24].

IV. Expected Results

TABLE II. PARTIALLY EXTRACTED CONVERSATION DATA THAT WERE TAGGED WITH SOCIAL CUES

Speaker	**Conversation data**	**Social cues**
Robot	Welcome.	Greetings
	How are you feeling today?	Self-disclosure elicitation
Visitor	I feel so-so.	Self-disclosure
Robot	Oh I see.	Acknowledge ment
	How about starting the counseling?	Suggestion
	What brought you here today?	Self-disclosure elicitation
Visitor	I feel so bored after work.	Self-disclosure
Robot	How about finding some hobbies to enjoy after work?	Suggestion
Visitor	What kinds of hobbies could I have?	Self-disclosure elicitation
Robot	How about jogging?	Suggestion
Visitor	Jogging sounds good!	Acknowledge ment
	There is a place to go jogging nearby my house.	Self-disclosure
Robot	That sounds really good.	Acknowledge ment

A. *Example of tagged conversation data*

A total of 654 conversation data comprising about 13080 sentences were collected using the dialogue data acquisition system [2]. Table II shows the example of conversation data that is tagged with different social cues.

B. *Expected results*

We expect that the final result of the research could suggest diverse social dialogue models shown in Figure 2 (Note that sequence of social cues is for illustrative purpose). The social dialogue model will be comprised of the chains and sequences of social cues. The sequences would be implemented with Python using Markov chain model [25], which is the mathematical systems that hop from one state to another.

In addition, we are planning to acquire more conversation data. We will recruit about 30 participants and obtain one-to-one conversation data rather than randomly collected conversation data. Half of the participants are professional counselors and others are not. After tagging the newly acquired conversation data, we would build social dialogue models. Finally, we can compare the randomly acquired conversation data to one-to-one conversation data.

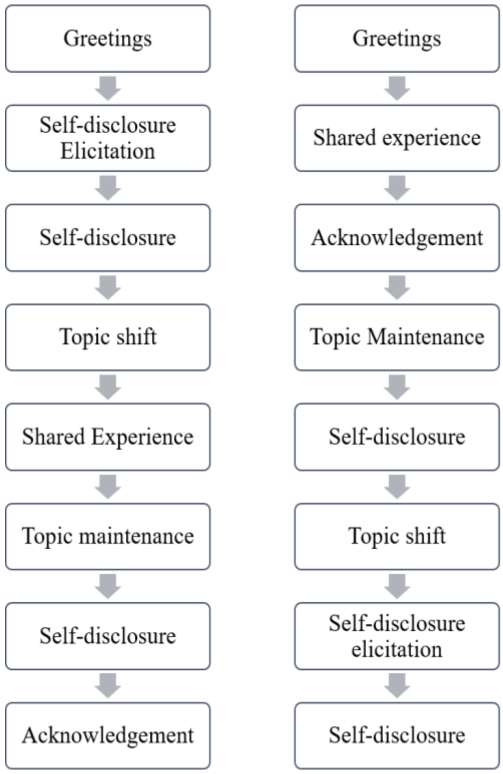

Figure 2 The expected results of social dialogue models.

V. Conclusion

To design the social dialogue model, we implemented the data acquisition system and collected conversation data. We are going to tag the acquired data with social cues based on the previous studies. Selected social cues are greetings, self-disclosure elicitation, self-disclosure, acknowledgement, shared experience, praise, topic management, termination, and non-verbal act. We will design the social dialogue model with the tagged data. With the designed social dialogue models, future research goal is to conduct user studies and find out more preferred social dialogue model.

Final results of the current study could propose the representative model of social dialogue for text-based chatting that could be applied in diverse conversational agents such as chatbots. In addition, social dialogue model could help build the natural conversations between humans and other robots.

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