Designing Social Dialogue Model for Human-Robot Interactions

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Figure 1: Overall procedure of the study.

ABSTRACT

Social dialogue between humans and robots increase in diverse contexts. To design the social dialogue model, we collected the conversation data with our own developed system. We recruited 80 participants who were randomly assigned to build and complete the conversations. After collecting the conversation data, we are currently in the process of tagging the data with social cues such as self-disclosure, acknowledgement, shared experience, and topic management. The implemented social dialogue could be applicable to diverse conversational agents such as chatbots.

KEYWORDS

Human-Robot Interaction, Social Dialogue Model, Social Cues, Discourse Analysis, System design, Data analysis

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1 INTRODUCTION

As the interactions between humans and robots increase, the need for social dialogue has also increased rather than simple fact-oriented dialogue [3]. 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) [13]. 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 human during text-based chatting.

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2 LITERATURE REVIEW

2.1 Conversations between Humans and Agents

People interact with diverse agents such as chatbots, social robots, and smart speakers, and embodied conversational agents. Agents perform diverse functions. They deliver the factual information to people [5]. For instance, agents report the weather condition, recommend the restaurants near the town, and give directions [11]. Meanwhile, agents could play a role as a conversational partner and have a small talk with people. To perform such function well, social aspects of interactions between agents and humans are important [3].

2.2 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 setting such as peer-tutoring and classroom to analyze the social dialogue [5, 15, 18, 20].

In the context of peer-tutoring [20] 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 [18]. Social dialogue was analyzed with conversational strategies such as self-disclosure, referring to shared experience, and praise. In the context of classroom, conversational data were examined with the standards of culture and ethnicity [6], which examined the differences of verbal and nonverbal behaviors between African American and American virtual peers [6].

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 [1] and museum [12]. Social dialogue between humans and REA (Real Estate Agent) was examined in the context of housing real estate [1]. Another study examined the message delivery of chatbots in the context of health counseling [14] The study questioned whether the chatbots should provide informational support or emotional empathy when counseling the personal health problems [14].

2.3 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 [7].

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 [20]. 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 [19]. Similarly, Brennan et al. also applied the concept of politeness to analyze the electronic conversations, but the hedge was the main standard of annotation [4].

To analyze the cultural differences between African American students and American students in social dialogue [6], phonological features of African American English (AAE) were applied [9]. In another study comparing the women's and men's speech, hedges were applied to analyze the conversations [10].

3 METHOD

3.1 Data Acquisition

We designed the dialogue data acquisition system that automatically acquires dialogue data from multiple users through Google form [13]. 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.

3.2 Analyzing the data

3.2.1 Procedure. We are currently in the process of preparing the tagging the collected conversation data. To minimize the inter-coder variability, three coders will be recruited and tag the conversation data [6]. To make sure that all coders have shared understandings of explicit standards and definitions of social cues, we plan to conduct the tagging training session in advance. In training session, specific examples of utterances for each social cue would be given to coders. The definitions of social cues will also be provided with example utterances.

3.2.2 List of social cues. Each social cue was selected based on previous studies: self-disclosure elicitation, self-disclosure, acknowledgement, shared experience, topic maintenance, topic deviation, topic shift, and non-verbal act (Table 1).

Categories	Social Cues
Initiation	Greetings
Rapport	Self-disclosure elicitation Self-disclosure
Empathy	Acknowledgement Shared Experience
Topic Management	Topic Maintenance Topic Deviation Topic Shift
Others	Non-verbal act

Table 1: The list of social cues used to analyze the conversation.

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 [18]. It occurs when people reveal their personal private information, emotional disclosure, and personal opinions. Through self-disclosure, conversational partners could build rapport and intimacy [1]. In addition, self-disclosure in the conversation could make the person to be perceived as more intimate and attractive [17]. ***Self-disclosure elicitation*** refers to the social cue that elicits the conversational partners to self-disclose themselves [2].

Acknowledgement and shared experience indicate 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 [8]. Acknowledgements are usually expressed explicitly with non-verbal behaviors such as eye gaze and head nodding [7]. Meanwhile, we adopted the cue of acknowledgement as verbal act in this study. ***Shared experience*** refers to the experience that the two interlocutors engage in or share with one another at the same time [20].

Diverse topics could exist in each individual conversation. To deal with such situation, we selected cues for Topic maintenance, Topic deviation and Topic shift. ***Topic maintenance*** refers to the utterances that were maintained previously in the conversation. ***Topic deviation*** refers to the utterances that go against general management of topics that have processed in previous conversations. Topic deviation is similar with the concept of the violation of social norms [20] in that it violates the general expectations of conversational partners. ***Topic shift*** refers to introduce new topics that were not mentioned in previous conversations. Topic management cues help analyzing the flows and structures of conversations.

Greetings functions as the initiation of the dialogue. Greetings are usually mentioned by the counselor as the first sentence of the conversations. ***Non-verbal act*** includes the expressions such as emoticons and ellipsis.

4 EXPECTED RESULTS AND CONCLUSION

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 are just 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

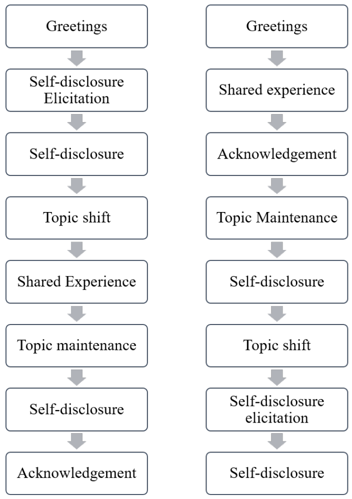

Figure 2: The expected results of social dialogue models.

model [16], which is the mathematical systems that hop from one state to another.

The results of the current study could propose the representative model of social dialogue for text-based chatting. 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. With the designed social dialogue models, future research goal is to conduct user studies and find out more preferred social dialogue model. The social dialogue models could be applied in diverse conversational agents such as chatbots. In addition, the social dialogue model could help build the natural conversations between humans and robots.

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