Discovering Chatbot’s Self-Disclosure’s Impact on User Trust, Affinity, and Recommendation Effectiveness

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Abstract

In recent years, chatbots have been empowered to engage in social conversations with humans and have the potential to elicit people to disclose their personal experiences, opinions, and emotions. However, how and to what extent people respond to chatbots’ self-disclosure remain less known. In this work, we designed a social chatbot with three self-disclosure levels that conducted small talks and provided relevant recommendations to people. 372 MTurk participants were randomized to one of the four groups with different self-disclosure levels to converse with the chatbot on two topics, movies, and COVID-19. We found that people’s self-disclosure level was strongly reciprocal to a chatbot’s self-disclosure level. Chatbots’ self-disclosure also positively impacted engagement and users’ perception of the bot and led to a more effective recommendation such that participants enjoyed and agreed more with the recommendations.

1 Introduction

As chatbots are increasingly communicating with people across various digital platforms, the chatbot-human conversations can evolve quickly to delving into more complicated and extended exchanges and disclosures of personal and emotional information. For example, while commercial assistant chatbots such as Amazon Alexa mainly engage in answering factual questions and providing information, a variety of social and health chatbots (Ravichander and Black, 2018; Lee et al., 2020) are probing into deeper levels of conversations to engage and to motivate the users. In recent years, developments in natural language processing and dialog systems have empowered chatbots with a greater capacity to engage in social conversations and learn from humans to take on languages for self-disclosures. However, what remains much less known is how and to what extent people respond to chatbot’s self-disclosures. Thus, we ask the following research questions. First, how do people reciprocate a chatbot’s self-disclosure? Second, how does a chatbot’s self-disclosure influence people’s engagement and perception of the bot? Lastly, how does a chatbot’s self-disclosure impact the effectiveness of the bot’s recommendations?

The present work designed a social chatbot to study the ways people reciprocate chatbots’ self-disclosure levels experimentally. Unlike prior work that only has one (Ravichander and Black, 2018) or two (Lee et al., 2020) self-disclosure levels, we designed three levels of chatbot self-disclosures: factual, cognitive, emotional, and built three chatbots with the three levels. A fourth both with adaptive self-disclosure level was also developed. To test this system, 372 MTurk participants were randomized to one of the four conditions to converse with the chatbot on two topics: movies, and COVID-19. As a result, we found that people reciprocated the chatbot’s level of self-disclosure. Besides, as the chatbot self-disclosed, people were more likely to engage in the conversation and perceive the chatbot as warm (e.g., friendly, kind). Lastly, we found that a high level of chatbot’s self-disclosure makes chatbot’s recommendations more effective. Our findings suggest that a high level of bot self-disclosure can serve as a driving force to enhance people’s self-disclosure and lead to more appreciated conversations. Further, the bot is perceived as more engaging and warmer when the bot displays a higher self-disclosure level. Lastly, emotional self-disclosure can play a significant role in whether people enjoy and agree with recommendations.

2 Related Work

Self-disclosure is the act of disclosing personal information such as personal opinions, thoughts,
beliefs, feelings, and experiences to others (Altman and Taylor, 1973). It is characterized by the levels of depth: peripheral disclosure of one’s information (i.e., factual disclosure), intermediate disclosure of one’s thoughts (i.e., cognitive disclosure), and core-level disclosure of one’s emotions (i.e., emotional disclosure) (Altman and Taylor, 1973; Barak and Gluck-Ofri, 2007; Lee et al., 2020; Malloch and Zhang, 2019). Self-disclosure has received considerable attention in interpersonal relations studies (Lee et al., 2020; Vondracek and Marshall, 1971). Here, we focus on the effects of self-disclosure on people’s reciprocity, engagement, perception towards the bot, and effectiveness of chatbot’s recommendations.

To begin with, reciprocity has been shown to be one of the most significant outcomes of self-disclosure (Jourard, 1971). Previous studies have demonstrated that self-disclosure induces reciprocity (Dindia et al., 2002; Barak and Gluck-Ofri, 2007). That is, as one party discloses themselves, the other party would be more inclined to self-disclose. Such effect of self-disclosure on reciprocity can also vary by the depth of disclosure. For instance, it was shown that people reciprocated to all levels of disclosure (i.e., informative, cognitive, emotional), but emotional reciprocity was the strongest (Barak and Gluck-Ofri, 2007).

Previous studies have also demonstrated that self-disclosure is related to interpersonal perceptions such as liking and trust of the conversational partner (Collins and Miller, 1994; Dindia et al., 2002; Berg and Derlega, 1987; Lee and Choi, 2017). The effect of self-disclosure on the perception of the partner can be applied to interactions with chatbots. Moreover, different levels of self-disclosure can induce various interpersonal perceptions. For instance, Ho et al. (2018) investigated the effect of self-disclosure on interpersonal perceptions, where self-disclosure was manipulated to either be factual (i.e., objective information about the discloser) or emotional (i.e., expression of emotions and feelings). Results revealed that the effects were more substantial after emotional disclosure than factual disclosure, especially on perceptions of partner’s warmth.

Lastly, self-disclosure of chatbots can lead to effective outcomes (Lee and Choi, 2017; Ho et al., 2018). To elaborate, Ho et al. (2018) revealed that when the conversational partner engaged in emotional disclosure, people were more likely to enjoy the interaction than when the partner engaged in factual disclosure. It was also found that when the agent engaged in self-disclosure, users were more likely to enjoy the interaction with the agent, which led to an enhanced level of satisfaction and further increased intention to use the system (Lee and Choi, 2017).

3 Chatbot Design

To answer our research questions, we designed and implemented a text-based chatbot with different levels of self-disclosure. We developed dialog sessions where the participants conversed with the bot twice about two distinct topics.

3.1 Chatbot System Architecture

We built the text-based chatbot system on top of Amazon Conversational Bot Toolkit (Cobot) (Khatiri et al., 2018). We sent each conversational turn to the AWS Lambda function as a RESTful API event request through the Amazon API gateway. The Natural Language Understanding module followed Gunrock 2.0 (an Alexa Prize Socialbot) (Liang et al., 2020), which contains critical components such as sentence segmentation, dialog act prediction, movie name entity recognition. The dialog management was adapted from Gunrock 2.0, in which participant attributes and dialog state were stored in DynamoDB, and a custom Finite State Machine manager was used to handle dialog state transition. The chatbot response generation consisted of predefined templates with different self-disclosure levels, an acknowledgement generator (A.1), and a question handler (A.2).

3.2 Bot Self-disclosure Design

To evaluate the effects of the bot’s self-disclosure, we randomly assigned participants to one of the four self-disclosure groups: factual (FD), cognitive (CD), emotional (ED), and adaptive (AD). The name of each group represents the highest self-disclosure level from the bot’s side. We designed the bot’s highest level at each turn to be as close to the corresponding group’s level as possible. There were only a few exceptions where the bot’s level was “none”, such as when the bot confirmed the recognized movie with the user if it was not confident.

In FD, the bot provided facts about itself (e.g., “I remember watching Titanic”) but did not share its thoughts or emotion. In CD, in addition to facts,
it revealed its opinion (e.g., how it thinks of social distancing) without sharing its emotion. In ED, the bot further shared its feelings about an actor or expressed empathy about the quarantine situation along with facts and thoughts. In AD, the bot started with a factual level, and at every turn, it detected the user’s disclosure level and matched its disclosure level to the user’s highest level of disclosure. This method of matching the bot’s disclosure to the highest level of the user’s self-disclosure was deemed reasonable given that the highest level of disclosure was reflective of the extent to which the user was willing to reveal to the bot.

### 3.3 Dialog Sessions

Each participant was asked to have two dialog sessions with the chatbot. In each session, the bot talked about one main topic with the participant, either Movie or COVID-19. Each session was composed of small talk (3.3.1) and recommendation (3.3.2). The procedure is shown in Figure 2. Moreover, it was critical to ensure the bot is responsive to the user’s input to keep the conversations engaging and natural. Hence, we implemented an acknowledgment generator and a question handler inspired by Gunrock 2.0 (Liang et al., 2020). The implementation details are shown in A.1 and A.2.

We used Movie and COVID-19 as the topics because most participants could easily relate to them and share their own information. We selected the two intrinsically different topics to mitigate topic bias. Watching movies is a common entertaining activity for people; thus, our results can be applied to similar domains such as movie recommendation chatbots. COVID-19 is a global pandemic, which is not only applicable to the majority of people but also relates to their well-being. Given that more recent works investigate building chatbots for emotional and behavior-change support during the pandemic by letting participants disclose their situation and concerns or by suggesting self-care tips (Miner et al., 2020), our study may be beneficial in these contexts.

#### 3.3.1 Small Talk

The small talks in both movie and COVID-19 sessions contained six to seven subtopics (Figure 1). The subtopics were the same across all groups, while the specific bot utterances differed depending on the corresponding self-disclosure level. The bot proposed subtopics turn by turn. In each turn, the bot first replied to the participant’s utterance to ensure the bot is responsive to the participants and then proposed the next subtopic in the same turn. In the movie session, the bot first asked a movie the users like (Appendix A.3) and continued the discussion by asking users’ opinions and providing fun facts. It then talked about users’ favorite actors and movie genre preferences. In COVID-19 session, the bot discussed participants’ experiences during the pandemic, such as activities they did during the quarantine, their opinions toward social distancing, and changes in shopping and diet.

#### 3.3.2 Recommendation

To investigate whether the bot’s self-disclosure impacts the recommendation’s effectiveness (RQ 3), we designed the bot to give recommendations on the related topics at the end of each session (A.4). In the movie session, the bot recommended a movie to the participants depending on the participants’ preferences collected in the Small Talk. In the COVID-19 session, the bot suggested self-care practices such as unplugging from technology and taking a walk.

![Figure 1: Small talk dialog excerpts of movie and COVID-19 sessions in FD, CD and ED.](image-url)
4 Participants, Measurement and Procedure

4.1 Recruitment and Participants

Participants were recruited on Amazon Mechanical Turk. To ensure the participants were eligible to talk about the study topics, we required them to proceed only if they were self-reported as movie lovers. We filtered out data from participants who did not finish the tasks, or encountered severe system errors, yielding a final sample of 372 participants. There were 106 participants in FD, 91 in CD, 85 in ED, and 90 in AD. We deployed our bot on a web interface where the participants could chat with the bot with text.

4.2 Procedure

Figure 2 shows the procedure. The participants were first randomly assigned to one of the self-disclosure groups (FD, CD, ED, AD). After filling in a pre-survey, they conducted two dialog sessions and filled in the same post-session survey after each session.

4.3 Measurement

4.3.1 Conversation Log Analysis

We utilized LIWC2015 (Tausczik and Pennebaker, 2010) to calculate the word length. Previous work has shown that word count is positively related to self-disclosure (Kreiner and Levi-Belz, 2019). Besides, to detect participants’ self-disclosure level that aligns with our scheme, we designed a self-disclosure classifier to detect participants’ self-disclosure level in each turn (Sec. 5).

4.3.2 Post-session Survey

After each dialog session, we measured user engagement, the participant’s perception of the bot (five constructs), and the bot’s recommendation effectiveness (three constructs). To ensure the robustness of the constructs, we used three measurement items with 5-point Likert scales (A.5) for each construct and calculated the average score to represent the construct’s score. Two open-ended questions were also asked to collect qualitative data on the participants’ opinions.

Recommendation effectiveness. “Recommendation agreement” is measured to see if the participants cognitively agree with the recommendation. We also measured “recommendation enjoyment” to understand if the participants emotionally enjoy listening to the recommendation. Even if people enjoy and agree with the recommendation, that does not necessarily mean they are motivated to take action, so we measured “recommendation motivation” to see how much people intend to follow the recommendation.

Engagement and perceptions of the bot. We measured “Engagement” to see how much people enjoy the conversation, which is an essential indication of people’s willingness to continue the conversation. “Closeness” was measured because a close relationship is often built by self-disclosure behavior. We measured “Warmth” to see how friendly/sympathetic/kind the participants think of the bot. We also measured “competence” to see how participants consider the bot’s ability to conduct a conversation; “Humanlikeness” to understand how much they perceived the bot as humans; “Eeriness” to see if they think the bot is weird.

Opinion questions. To understand the participants’ opinions on the conversation, we asked two open questions at the end of the survey: “Which part of the conversation did you like best?” and “Which part of the conversation did you like least?”

5 Self-disclosure Level Classifier

To identify participants’ self-disclosure levels, we used a BERT-based model (Devlin et al., 2018) and fine-tuned it with our own annotated dataset.

5.1 Annotation Scheme

We designed a single-label annotation scheme with four labels: none, factual, cognitive, and emotional. Since one participant’s utterance may include multiple sentences with different self-disclosure levels,
we first segmented it into sentences using NLTK sentence tokenizer and then annotated each sentence segment.

Table 3 shows the annotation schemes. “None” self-disclosure included opening, back-channeling, hold, command, and question. “Factual” and “cognitive” levels depended on contextual information. When the bot asked a question, and the participant shares opinions, it was considered “cognitive”. However, when the user only shared factual experience to a bot’s question, answers yes or no to a yes/no question, or selects a preference without any explanation, it was annotated as “factual”. As for “emotional” level, when participants’ emotions (e.g., revelation of feelings, usage of exclamation marks, interjection, emoji, and emoticon) were contained in the message, it was considered “emotional”.

5.2 Dataset

We deployed a pilot study of 41 tasks (14 FD, 13 CD, and 14 ED) to collect training data. To ensure annotation reliability, two dialog experts (co-author of this paper) annotated 76 randomly selected sentence segments and reaches a Cohen’s kappa of 71.1, indicating substantial agreement. After the two annotators discussed annotation discrepancy and reached a consensus, one annotator annotated 535 more segments, resulting in a total of 611 annotated sentence segments (263 factual, 200 cognitive, 90 emotional, 58 none). The annotated samples were then split into training/development set with a 75/25 ratio. Since the labels are highly imbalanced, we balanced the training data by oversampling minority classes to the same amount as the majority class, resulting in a total of 800 training examples (200 examples for each label).

5.3 Classifier

To build a self-disclosure classifier, we started with a BERT-based neural model (bert-base-cased) pre-trained with Wikipedia and BookCorpus (Devlin et al., 2018), and fine-tuned it with the 800 training examples for the classification task. The model used 12 layers with 12 attention heads and a hidden size of 768. The fully connected layers used a dropout rate of 0.1.

As the self-disclosure levels were context-dependent, we included the bot’s utterance of the last turn, and the previous user utterance segments of the current turn in the input to classify each user utterance segment. Inspired by (Yu and Yu, 2021)’s method of context representation, we appended the bot’s last utterance ([CLS] bot_last_turn), the user’s utterance prior to the target segment of the same turn (user_prev_segs), and the target user segmented text (user_cur_seg) as [CLS] bot_last_turn : user_prev_segs [SEP] user_cur_seg [SEP]. If there was no previous user segment, we then put an EMPTY token in the user_prev_segs. After training, the model reached a macro average F1 score of 79.6% (precision 78.8%, recall 80.5%). Considering some types of emotional self-disclosure were context-independent and can be easily distinguished, we patched the classifier with rules to en-
hance the performance. We used the emot (Shah, 2020) library to detect emoji, and regular expressions to detect exclamation mark and interjections such as ha, wow, lol. This led to a slightly improved performance with a macro average F1 score of 81.7% (precision 80.4, recall 83.2%).

The confusion matrix is shown in Figure 4. We found that most of the misclassifications occurred between adjacent levels. For example, sentences with “emotional” levels were sometimes classified as “cognitive” but seldom classified as “factual”, and the ones with “cognitive” levels were occasionally detected as “factual” but never detected as “none”. This might be due to the ambiguity between adjacent levels. For example, in this case: Bot: Do you think your diet has changed since you’ve been staying at home a lot? User: Yes, less fast food., the user provided explanation on how his/her diet changes to a yes/no question, so it was labeled as “cognitive”, but the model detected it as “factual” potentially because the explanation was also a fact.

In the dialog system, the classifier detected participants’ self-disclosure level in real-time whenever the system received participant’s utterance. If the participant utterance had multiple sentence segments in the same dialog turn, the classifier first detected self-disclosure level for each segment (segmented with NLTK sentence tokenizer) and then selected the highest self-disclosure level to represent the self-disclosure level for that turn.

6 Effect of Self-disclosure

6.1 Self-disclosure Reciprocity (RQ1)

To understand how participants reciprocate a chatbot’s self-disclosure, we measured users’ self-disclosure level, word length at dialog turn level. As described in 3.2, there were some turns where the bot’s disclosure levels are none. To make the analysis more robust, we combined all dialogs in FD, CD, ED and categorized the results based on the bot’s turn level self-disclosure instead of the self-disclosure group.

To evaluate how users reciprocate to chatbot’s self-disclosure levels, we first identified users’ self-disclosure levels of each turn with a self-disclosure classifier (Section 5). Then we performed several 2-by-4 chi-square tests to examine the relationship between bot’s and user’s levels of self-disclosure. We found that users significantly reciprocated the bot’s self-disclosure (Figure 5). In movie dialogs, users’ responses following bot’s cognitive and emotional self-disclosure were both found to display higher ratio of cognitive and emotional levels than after bot’s factual self-disclosure ($\chi^2(3, N = 1855) = 21.63, p < .001$, $\chi^2(3, N = 1788) = 28.31, p < .001$). In COVID-19 dialogs, the reciprocity effects were more salient between adjacent levels. As the bot’s self-disclosure levels increased, the users showed an increased likelihood of higher levels of self-disclosure. ($\chi^2(3, N = 1349) = 8.87, p < .05$ between cog. and fact., and $\chi^2(3, N = 1205) = 20.86, p < .001$ between emot. and cog.) This suggests that users reciprocate the bot’s self-disclosure levels. Examples of how users reciprocated the bot’s self-disclosure levels are presented in Figure 6.

It should be noted that the most dominant user disclosure level was not always synchronous with the bot’s self-disclosure level. As the bot’s disclosure level increased, the most dominant level of user’s self-disclosure was usually one or two levels lower than the bot’s. That is, matching the bot’s high level of self-disclosure may have been difficult for users. However, the bot’s high self-disclosure level may still serve as a driving force to encourage users to disclose more. This may suggest that when the goal is to encourage people to disclose more, it may be more effective when the bot uses higher self-disclosure levels than simply matching the user’s disclosure level.

Word count of user responses after bot’s cognitive and emotional disclosure turns were both found significantly higher than FD’s ($p < 0.01$) in
6.2 Engagement and Perception of Bot (RQ2)

We performed several two-tailed t-tests between groups and found that the chatbot’s self-disclosure significantly affected users’ engagement and perceived warmth (Figure 7). We also found a significant interaction effect between topic and self-disclosure level for most of the constructs, so we evaluated the results of the two topics separately.

6.2.1 Engagement

In movie sessions (Figure 7a), post-hoc analysis showed that both cognitive and emotional disclosures led to higher user engagement ($p < .05$ for both) than factual self-disclosure, while the user engagement did not differ between cognitive and emotional disclosure. It was also found that user engagement increased when bot’s movie preference was similar to theirs. The following example demonstrates how participants reported their opinions on the bot’s disclosure of opinion, preference, and emotion: “I liked how the Bot asked me questions about myself and also included its own opinions and views.” (P05, CD, movie); “I liked The part that the BOT told me comedy is its favorite genre.” (P93, ED, movie); “I liked that The bot seemed to have more feelings. ” (P305, ED, movie)

In COVID-19, the bot with emotional self-disclosure was found significantly more engaging than the one with cognitive ($p < 0.01$). This might be because COVID-19 was an issue that people suffered from, so people may have expected the bot to show more emotions and empathy than when discussing movies. For instance, two participants commented: “I liked when bot was recommending something based on what was relevant to the conversation. It felt like it was reaching out and giving good emotional feedback.” (P137, ED, COVID-19).

“I liked that the bot showed emotion feeling towards people dining out.” (P137, ED, COVID-19).

6.2.2 Perceived Bot Warmth

The effect of the bot’s self-disclosure on user perception of the bot’s warmth was significant. Post-hoc analyses showed that for both movie and COVID-19 sessions, the bot was perceived warmer in emotional disclosure ($p < .05$) than in factual. The effect of emotional self-disclosure was even more significant than cognitive disclosure in COVID-19 sessions ($p < .05$). This may be because COVID-19 was related to people’s immediate welfare, and the bot’s emotion revealed its caring for people. As noted by a participant, the bot was more appreciated when it showed emotions: “I loved when the bot empathized with being stuck at home. Very relatable.” (P240, ED, COVID-19)

Also, in movie sessions, the participants perceived the bot with cognitive disclosure warmer than the one with facts only. We think it is because, in movie sessions, the bot revealed its preference towards movies, actors, and genre. Moreover, the results showed that users in adaptive disclosure condition perceived the bot to be less warm than users in emotional disclosure condition ($p < 0.1$ in movie, $p < 0.5$ in COVID-19), especially in movie dialog, the adaptive bot was perceived to be less warm than when the cognitive bot ($p < 0.5$). This may be because the adaptive bot was more “passive” in disclosing itself than the cognitive and emotional bot. Instead of taking the initiative to disclose more about itself, the adaptive bot only disclosed more if the user did so this may
have led to lower perception of its warmth. Therefore, we suggest that future dialog design starts with a high self-disclosure level to enhance users’ experience.

6.2.3 Perceived Closeness, Competence, Human-likeness, and Eeriness

In movie dialogs, the perceived closeness between humans and the bot was significantly higher when the bot engaged in emotional self-disclosure than the bot’s factual disclosure ($p < .05$). We also found that people perceived the bot to be more competent in movie sessions when the bot showed cognitive or emotional self-disclosure ($p < .05$). This means that sharing opinions or emotions made the conversation more coherent and reasonable. Although there was no significant effect of human-likeness in separate topics, we combined results from both sessions and found that the emotional bot was perceived more humanlike than the factual bot ($p < .05$). There was no significant difference in perceived eeriness across conditions.

6.3 Effectiveness of Recommendation (RQ3)

Several two-tailed t-tests between groups were conducted, and the results showed that there was a significant effect of bot’s emotional self-disclosure on recommendation enjoyment ($p < .05$) and agreement ($p < .05$), compared to bot’s cognitive self-disclosure. This means that people were more likely to enjoy and accept a bot’s recommendations when a bot engaged in emotional disclosure than when the bot disclosed cognitive information. However, there was no significant effect on recommendation motivation. This might be because the recommendation did not apply to the user’s situation (e.g., no time to watch a movie, or the weather was not suitable for a walk).

7 Discussion

Our work departs from prior work in the following ways. First, we investigated the effect of a bot’s self-disclosure with three different self-disclosure levels instead of just one (Ravichander and Black, 2018) or two (Lee et al., 2020), and thus provides a more nuanced picture of how bots can leverage self-disclosure. Second, the user reciprocity was measured on finer-grained self-disclosure levels to see how users adapt their levels to the bot’s levels. Third, to the best of our knowledge, our work is the first to examine how different self-disclosure influences recommendation effectiveness. Lastly, we studied the effect of passively adaptive self-disclosure compared to consistent ones and showed that bots that consistently have high disclosure were perceived warmer than those who passively followed the users’ levels. We believe our work provides a better understanding of how a bot’s self-disclosure can be leveraged to encourage users’ self-disclosure and engage users.

8 Conclusion

This study experimentally studied how people reciprocate chatbots’ different levels of self-disclosure with a text-based social chatbot. We showed that peoples’ self-disclosure levels were positively correlated to the chatbot’s self-disclosure level. Also, we found that higher levels of self-disclosure led to more engaging conversations and warmer bot perception. Lastly, emotional self-disclosure significantly enhanced people’s enjoyment and agreement when making recommendations.
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A Appendix

A.1 Acknowledgement Generator

To acknowledge participants’ general utterances that were not questions, the Blender model was used in the first place to generate more engaging responses. If no response was generated, we then used hand-written acknowledgment templates designed either specifically for each dialog state or very common participant intents. For example, if the bot asked the participant about his/her favorite actor and the participant answers “Jennifer Aniston”, the bot would answer “I see, I like Jennifer Aniston too.” If the participant said “I don’t know”, which is a common intent, the bot would generate “That’s okay”. If the participant said, “That’s interesting!”, the bot would said “I’m glad you like it.” For participants utterances that were not common intents, the bot replied with general acknowledgment such as “I see.”, “Gotcha.”

A.2 Question Handler

When handling participant’s questions, we used backstory-database (Liang et al., 2020) and Amazon EVI \(^1\) to handle questions associated with the bot’s persona and factual questions, respectively. If no answer is retrieved, we then used a text generation model, Blender (Roller et al., 2020), to generate answers. By leveraging the model, the bot could handle a wider range of participant input and generated diverse responses. The model was an encoder-decoder model with 2.7B parameters trained with collected human conversational data. If no response was generated, the bot generated a rephrased answer to express that the bot does not have an answer. For example, if the participant asked, “How long will the coronavirus last?”, the bot would answer “I don’t know how long will the coronavirus last.”. If the bot failed to generate a rephrased answer, it replied with a general answer such as “Sorry, but I don’t know much about that.”

A.3 Movie Name Grounding

Since the discussion about a movie takes half of the turns, to ensure the conversation is not too short, if the bot fails to recognize the mentioned movie, it would ask users to name another movie until it recognizes it and starts discussing it.

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\(^1\)https://www.evi.com/
| Construct                | Measurement item                                                                 | Scale                  | Cronbach's alpha |
|-------------------------|----------------------------------------------------------------------------------|------------------------|------------------|
| Recommendation enjoyment| I like the bot's recommendation at the end.  
|                         | I enjoy hearing the bot's recommendation at the end.  
|                         | The bot's recommendation at the end sounds interesting to me.                   | 1=strongly disagree, 5 = strongly agree | 0.937            |
| Recommendation agreement| It is useful to follow the bot's recommendation.  
|                         | It is wise to follow the bot's recommendation.  
|                         | It is beneficial to follow the bot's recommendation at the end.                | 1=strongly disagree, 5 = strongly agree | 0.947            |
| Recommendation motivation| I plan to follow the bot's recommendation.  
|                         | I intend to follow the bot's recommendation.  
|                         | It is my intention to follow the bot's recommendation.                       | 1=strongly disagree, 5 = strongly agree | 0.968            |

Figure 10: Constructs and measurement items for engagement and people’s perception of the bot.

| Construct                | Measurement item                                                                 | Scale                  | Cronbach's alpha |
|-------------------------|----------------------------------------------------------------------------------|------------------------|------------------|
| Engagement              | How engaging did you feel during the conversation?                              | 1=unappealing, 5=engaging | 0.907            |
|                         | How enjoyable did you feel during the conversation?                             | 1=unpleasant, 5=enjoyable |                  |
|                         | How interesting did you feel during the conversation?                           | 1=boring, 5=interesting |                  |
| Perceived closeness      | How close did you feel with the bot?                                            | 1=distant, 5=close      | 0.946            |
|                         | How connected did you feel with the bot?                                         | 1=unconnected, 5=connected |                  |
|                         | How associated did you feel with the bot?                                       | 1=disassociated, 5=associated |                  |
| Perceived bot warmth     | How friendly did you find the bot?                                              | 1=distant, 5=friendly   | 0.808            |
|                         | How sympathetic did you find the bot?                                            | 1=unsympathetic, 5=sympathetic |                  |
|                         | How kind did you find the bot?                                                  | 1=cold-hearted, 5=kind  |                  |
| Perceived bot competence | How coherent did you feel during the conversation?                              | 1=incoherent, 5=coherent | 0.864            |
|                         | How rational did you feel during the conversation?                              | 1=irrational, 5=rational |                  |
|                         | How reasonable did you feel during the conversation?                            | 1=reasonable, 5=unreasonable |              |
| Perceived bot humanlikeness| How human-like did you find the bot?                                            | 1=fake, 5=human-like    | 0.932            |
|                         | How natural did you find the bot?                                               | 1=machine-like, 5=lifelike |                  |
|                         | How lifelike did you find the bot?                                              | 1=artificial, 5=enjoyable |                  |
| Perceived bot eeriness   | How weird did you find the bot?                                                 | 1=normal, 5=weird       | 0.890            |
|                         | How creepy did you find the bot?                                                | 1=pleasant, 5=creepy    |                  |
|                         | How freaked out did you find the bot                                            | 1=ordinary, 5=freaked out |                  |

Figure 11: Constructs and measurement items for recommendation effectiveness.