

Repair in a task-oriented chatbot, and the question of communication skills for AI

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Introduction

Chatbots are getting ever more pervasive to everyday life. Grand View Research (2021) estimates the global chatbot market at USD 430.0 million in 2020 and to have an growth rate of 24.9% annually till 2028. Using machine learning algorithms to chat with humans and learn from these interactions, chatbots can be found in a wide range of settings, including healthcare, retail, travel and tourism.

Human-chatbot interactions thus represents a form of social interaction carried out online, also described as computer-mediated discourse (Herring, 2004). Like web chat, chatbots are a ‘lean’ medium of conversation in that these interactions are deprived of the visual and auditory cues which are part face to face interaction (Daft & Lengel, 1986). However, the ‘lean’ properties of chatbot mediated conversation go beyond that of normal chat in that the contributions of one conversational partner are processed, interpreted and responded by a computer rather than another human. These interpretations and responses depend on the bot’s ability to *understand* natural language input, to *generate* adequate responses and to *repair* when there is evidence understanding is lacking. However, these three steps pose a range of challenges. Understanding is challenging because “people are inconsistent, and their lives are disorderly. Their situations, circumstances and aspirations change. They get tired and hungry, glad or sad [...] And sometimes they have no clue what they really want” (Hantula et al., 2021). A bot will have to respond to these changing circumstances understand the user’s intent, despite the potential variations in which this intent is expressed. Secondly, the bot has to generate language that responds correctly to users’ intents, which in most dialogue systems is done through pre-compiled sentences or templates (Di Lascio et al., 2020). And finally, as Collins (2018) points out, ‘repair’ is a fundamental feature by which humans deal with communication that is less than perfect and thus is fundamental to interactions with AI driven systems, too.

However, when interacting with bots, humans cannot necessarily rely on the same models of communication than in face to face social interaction. As research by Luger & Sellen (2016) on users’ expectations and experience of conversational agents has found, technically more skilled participants were better prepared to prepare new mental models of interaction than lower skilled participants whose expectations did not change and who were more likely to get frustrated by their interactions. This raises the question as to whether users transfer strategies from face to face modes of interaction into their actions with AI and whether traditional models of communicative competence (e.g. Canale & Swain, 1982) need to be adapted to different forms of conversational AI.

With these insights in the background, this paper takes a user-centric perspective to investigate repair, described here as users’ efforts for pre-empting or addressing intent interpretation issues in a task-oriented chatbot interactions. These insights have important implications for how communicative competence for conversational AI should be described. These issues will be discussed in the conclusion to this paper.

Literature review

The term ‘repair’ is originally derived from conversation analysis. Repair was first described by Schegloff et al. (1977) as a “self-righting mechanism for the organization of language use in social interaction” (p. 381), whereas Seedhouse (2005) defines repair as “the treatment of trouble occurring in interactive language use” (p. 168). In ordinary conversation, repair can be used by speakers to address problems in hearing, speaking and understanding. In conversation with a text-based chatbot, repair is often carried out to address issues with interpreting user input. When the bot struggles with doing so, users need to use repair in order to achieve the task they have set out to do.

In their typology of repair, Schegloff et al. (1977) distinguish between self-initiation of repair (repair initiated by the speaker who is the cause of the trouble source) and other-initiation of repair (repair initiated by the another speaker). They also distinguish self-repair (repair completed by the speaker who is the cause of the trouble source) and other-repair (repair completed by the another speaker), emphasizing also that some repairs do not have a successful outcome at all. Speakers use a variety of means to other-initiate repair, such as signals of misunderstanding (e.g. Hugh, What?), question words (who?, when?) which may be combined with a partial repeat of the trouble source.

Albert & de Ruiter (2018) argue that the notion of repair as introduced by conversation analysts such as Schegloff et al. (1977) constitutes a “minimal notion of shared understanding as progressivity” (p. 281) which consciously does not focus on context. However, they also argue that observing repair provides rich insights into the sources of the misunderstanding, which may include “contextual problems of propriety or transgression” (p. 303). This paper will focus on both: whilst it will identify repair sequences in chatbot dialogue through the lack of progressivity, it will also attempt to provide insights into users’ understanding of the sociolinguistic environment of these interactions with the bot, including their ideologies and perceptions of language.

Repair has been subject to a wide range of investigations in specific contexts of interpersonal communication, such as the classroom (Dippold, 2014; Montiegel, 2021) and in workplace interaction (Oloff, 2018; Tsuchiya & Handford, 2014). In computer-mediated environments, repair has so far primarily been investigated in the context of webchat, focusing for example on the repair morpheme *- in gaming chat (Collister, 2011), German web chat (Schönfeldt & Golato, 2003), library web chat (Koshik & Okazawa, 2012) and facebook chat (Meredith & Stokoe, 2014). This research found that that repair in online chat shows is organised differently to ordinary conversation due to differences in the sequential flow of messages. Moreover, users do not have access to the same set of resources to accomplish social interactions as in spoken conversation (e.g., prosody), They do however compensate with other ways of creating meaning (such as (*- as a repair phoneme), and general principles of repair from ordinary conversation (e.g. the preference for self-repair) still apply.

Repair has also been the subject of research in interactions between humans and embodied robots as well as chatbots. For example, Beneteau et al. (2019) investigated communicative breakdowns between Alexa and family users. They showed that the onus on providing ‘repair’ when communication broke down lay with users. Users deployed a range of strategies to perform repair, e.g., using prosodic changes, over articulation, semantic adjustments / modifications, increased volume, syntactical adjustments, repetition.

Research on human interaction with text-based chatbots confirms that the burden of repair lies primarily with the user. Analysing transcripts of interactions between users and a task-oriented chatbot, Li et al. (2020) investigated the relationship between different types of non-progression and user repair types. They found that bot users were most likely to abandon the conversation after three instances of non-progress., which were caused by misrecognition of user intents on one hand, and non-recognition on the other. Users drew on a range of strategies for dealing with non-progress, including quitting, changing the subject temporarily, abandoning the bot service, temporarily quitting the conversation, switching the subject and various forms of reformulating messages (self-repair), e.g., rephrasing, adding, repeating or removing words, using the same words, new topics etc.

Ashktorab et al. (2019) investigated user preferences for the repair strategies used by a banking chatbot in an experimental setting, finding that users preferred the bot to initiate repair by providing options of potential user intents. Users also favoured assisted self-repair (e.g., explaining which keywords contribute the bot’s lack of understanding) over other strategies. However, users’ strategy preferences depended on other factors such as their social orientation towards chatbots, their utilitarian orientation, their experience with chatbots and technology and the repair outcome.

Følstad & Taylor’s study (2020) centred on the bot’s strategies for initiating repair and asked whether a chatbot expressing uncertainty in interpretation and suggesting likely alternatives would affect chatbot dialogues at message, process and outcome level. They found that initiating repair in this manner substantially reduced falls positive answers – responses that are not relevant to a customer request – and fallback responses offering escalation or explicitly expressing misunderstanding – whereas the number of relevant responses remained stable across both conditions.

Whilst this literature review shows that there is already a small body of studies on repair in computer-mediated communication generally and in human-bot interaction more specifically, users’ strategies for dealing with repair and working themselves out of bot misunderstanding have not yet been sufficiently explored, in particular from a primarily qualitative perspective. Besides’ Li et al.’s (2019) study on repair types and non-progress, the only other qualitative evaluation on user strategies for overcoming problems in interaction with bots focuses on voice bot interaction. Myers et al. (2018) identified ten different user tactics, the most frequently ones used being hyperarticulation (speaking louder, slower or more clearly), adding more information, using a new utterance to express the same intent, and simplification.

This study compliments builds on these insights by investigating user repair strategies in a text-based chatbot. In doing so, this study will not only describe the ‘technicalities’ of repair, but also draw conclusions into users’ understanding of the AI-mediated environment. I will use this to then discuss implications for skills development.

Objectives

The objective of this paper was to track how users of a task-oriented chatbot navigate through episodes in which the bot lacks understanding of or misunderstands their intents through conversational repair. As this paper was exploratory, no more detailed research questions were asked. However, the analysis has revealed possible further questions which could be explored with a larger dataset gathered ‘in the wild’ rather than a simulated setting.

Data

Asa, the bot

The data for this paper are drawn from a research project conducted jointly with start-up company spryt.com. SPRYT have developed an intelligent patient scheduling system which allows patients to schedule medical appointments through Whatsapp via a text-to-text interactions. Patients interact with a digital receptionist – the chatbot – called ‘Asa’ to schedule, reschedule or cancel appointments, respond to a medical screening questionnaire or ask questions. At the stage of the data collection, Asa was developed to the stage of being a ‘minimum viable product’ – it was functionable but had not yet been tested with real patients and had not yet engaged in algorithmic learning from real patients’ interactions.

Dataset

The analysis is based on 36 interactions between users and the appointment scheduling bot. These interactions took place in a simulated setting as part of user research of the system pre-deployment. Ten of the interactions were created during the first phase of the project. In this phase, user experience interviews were conducted during which users interacted with the bot and were asked to talk in detail about their perceptions of the bot’s speech turns and of the system as a whole. 26 interactions were created in phase two of the project. In this phase, users interacted with Asa to complete a booking at a minimum. In addition, users were also

instructed to complete other tasks, such as rescheduling, cancelling, or asking a question. Subsequent to their interactions, users reported their opinions about Asa through a questionnaire after their interactions. For the purpose of this analysis, only the interactions in themselves will be considered.

Participant recruitment and demographics

Participants were recruited through the researchers' social media channels as well as the university's experimental platform. As a result, the majority of participants in the interview phase were UG and PG university students, in addition to two professionals who took part in the research due to professional interest in chatbot development. In the questionnaires stage, the majority of participants (45%) were between 18 and 24 years old. There was also a lack of diversity with respect to other demographic factors, such as users' language status and ethnicity.

Data analysis and results

Analytical approach

Data analysis was exploratory and only loosely theory-guided at the start of the project. Whilst the researcher was aware of the possible relevance of repair for chatbot interactions due to her own previous work (Dippold et al., 2020) and her reading of the literature, the analysis did not focus on repair on the outset. However, after an initial reading of the conversational data and exploratory annotations in a qualitative analysis software programme (Nvivo), repair emerged as a possible focus in the analysis.

Stages of analysis

The analysis took place in five subsequent stages. These stages were not pre-determined at the outset; rather, each step was guided on the previous and added an additional layer of evidence. Each of these steps will be discussed in detail below, with examples from the data then allowing a more detailed exploration of the results.

Step 1: This step focused on the identification of all conversation sequences in which there was a lack of progression. A sequence was considered to have ended when the bot gave a relevant response. This resulted in the identification of 75 repair sequences in total.

Step 2: In this step, all sequences were further coded into those in which the trouble source was a user turn and those in which it was a bot turn. They were then further annotated using Schegloff et al.'s (1977) system of description of repair as self-initiated or other-initiated self-repair or self-initiated or other-initiated other-repair (see table 1):

		self-initiated	self-initiated	other-initiated	other-initiated
User turn	72	7		65	
Bot turn	3			3	
		self-repair	other-repair	self-repair	other-repair

Table 1: Types of repair

Table 1 shows that the vast majority of repairs are of trouble sources in user turns (72), most of which are other-initiated but self-repaired. This study will focus on these on other-initiated self-repair of user turns as these are representative examples of the bot misunderstanding, or not understanding, the user's intent.

Step 3: In the third step, the repairables in each repair sequences were classified. This resulted in the identification of five different repairable types were identified, as illustrated by Table 2.

Repairable types	Example
Choice: user input of bot-prompted information, e.g., desired appointment times	15/02/2022 at 2pm

Repairable types	Example
Information question: user-initiated information questions, e.g. about the procedure	What I should do
Request: explicit requests to the bot	Oh no, it turns out
Other: e.g., user affirmations of understanding, user self-disclosure, user expressions of understanding	Hi Asa! Im FirstN

Table 2: Repairable types

Table 2 shows that a large proportion of the repairables which result in bot-initiated user self-repair consists of user inputs of information that was originally prompted by the bot. In frequency, these are on par with user-initiated information questions, for example about the procedure, parking information etc. The third main category are user requests to the bot which are often at the start of a new transactional sequence, e.g., to reschedule an appointment.

Step 4: In this stage, the eight main strategies for user self-repair were identified and the data were fully coded according to the definitions below (see table 3):

Self-repair strategies and definitions	Examples	Count
Rephrase: the user rephrases the original turn	<i>Sorry, I didn't quite get that. I'm still learning. Can you please rephrase the date/time you provided? Thanks, Asa</i> Tuesday would be best <i>Sorry, I didn't understand that. Can you say that in a different way?</i> Can I have the scan on Tuesday	42

Self-repair strategies and definitions	Examples	Count
Accommodation: the user uses a bot prompt from the previous turn to construct their turn	What I should do before the mri ? <i>Sorry what do you want to do? Here is how I can help. Just type: *Schedule / Reschedule *Cancel* *My appointments* - to see your upcoming appointments *Prep* - for info on how to prepare for your appointment *FAQ* - for our frequently answered questions page *General* - for general info (opening times, phone no., directions/maps etc.) *Admin* - to speak to the medical reception team</i> Prep <i>The scan will be 20-45 min, and you will remain fully dressed * Unless we let you know otherwise, you can eat and drink as normal and take any prescribed medication * You're welcome to bring a friend or a relative with you * The radiography team will explain the process once you arrive * Do you have any other questions or concerns about what to expect on the day? please answer with yes/no</i>	41
Change choice: the user changes a choice they had originally made, e.g., their desired appointment time	Morning <i>Oops, something went wrong. An unexpected error was detected and reported to the support department. Please try again a bit later, and if the issue persists contact admin for further assistance. Thank you, Asa</i> Afternoon <i>Oops, something went wrong. An unexpected error was detected and reported to the support department. Please try again a bit later, and if the issue persists contact admin for further assistance. Thank you, Asa</i>	25

Self-repair strategies and definitions	Examples	Count
Restate purpose: the user restates the purpose of their request, e.g., their desire to book an appointment	<i>Please select a date and time for your appointment 18:00 19:00</i> <i>None 7pm Sorry, but I could not reschedule the appointment.</i> <i>Please try again a bit later, or try re-booking with different date/time. If however you are still facing issues I can connect you with someone from the clinic to help you out, just type – speak to someone. Thanks, Asa I meant 19:00 Did you mean? google *calendar* link for my scheduled appointment *faq* - frequently asked questions restart *None* of these None of these Apologies, bear with me. I'm still learning. Can you rephrase? Can I reschedule No worries. Please let me know the number of the appointment you would like to reschedule: 1. Screening on Thu 09 Jun '22 at 19:00</i>	8
Repeat: the user repeats the original item	can i bring a friend to the appointment <i>Did you mean? *schedule* appointment clinic's *location* you are *welcome* *None* of these ? Sorry, I didn't understand that. Can you say that in a different way? can i bring a friend to my appointment? Sorry, I still can't understand your question. Would you like to speak to a member of our team? no thank you</i>	8
Other: e.g., users directly addressing the bot, users' affirmative or non-affirmative answers to bot questions	wheelchair access <i>Sorry, I still can't understand your question. Would you like to speak to a member of our team? yes, please Are you trying to say? *yes* or *no* *hello* made a *mistake* *None* of these</i>	8

Self-repair strategies and definitions	Examples	Count
Change topic: the user changes the topic / focus of the interaction	What is the appointment for <i>Did you mean? find *my appointments* clinic's *location* *schedule* appointment *None* of these</i> What is the appointment for? <i>Sorry, I didn't understand that. Please say that again</i> How long will the appointment take? <i>I am sorry, I still do not understand your question. Would you like to talk to someone from our team?</i>	7
Late accommodation: the user uses a bot prompt from an earlier bot turn	<i>Okay. Please choose a preferred time of day: * Morning (8am-12pm) * Afternoon (12pm-5pm) * Evening (5pm-8pm) * Any (8am-8pm) am</i> <i>Sorry, but I could not reschedule the appointment. Please try again a bit later, or try re-booking with different date/time. If however you are still facing issues I can connect you with someone from the clinic to help you out, just type - speak to someone. Thanks, Asa</i> Morning <i>I'm sorry, but there are no available time slots left on this date. Please specify a different date. Thanks, Asa</i>	6
Question: the user asks the bot a question	<i>What date works for you? As soon as possible I'm happy to assist with booking, rescheduling an appointment, and you have some more options at the menu above</i> What options are there? <i>I'm happy to help you with booking, rescheduling, and you can find more options at the menu above.</i>	6

Table 3: Users' strategies for self-repair

Table 3 shows a clear hierarchy of repair strategies favoured by users: users most frequently rephrase their original turn, but this is closely followed by accommodation strategies in which users use a prompt provided by the bot in a previous turn. Other strategies used include changing their original choices, presumably in the hope that a new choice will be understood, restating the purpose of their original request and repeating the original turn.

Step 5: The final stage of the analysis centred upon classification of bot responses following user self-repair.

The purpose of this analysis was to identify how successful users' repair strategies were leading to progress within the conversation. The bot's follow-up turns were coded against Følstad & Taylor's (2021). qualitative framework for the analysis of chatbots, to which a fifth category of 'no response' was added (Table 4)

Response type and definition	Examples	Count
Relevant response: The turn is relevant for the user message.	need help Here is how I can help. Just type: *Schedule / Reschedule / Cancel* - to manage appointments *My appointments* - to see your upcoming appointments *Prepare* - for info on how to prepare for your appointment *FAQ* - for our frequently answered questions page *General information* - for general info (opening times, phone no., directions/maps etc.) *Speak to someone* - to speak to the medical reception team	86
False positive: The turn is irrelevant for the user message.	I think you don't understand the question.. Do you have a general info question or a question about the appointment or procedure?	18
False negative: The turn erroneously indicates the user message to be out of scope.	I meant 19:00 Did you mean? google *calendar* link for my scheduled appointment *faq* - frequently asked questions restart *None* of these	47
Out of scope: The turn correctly indicates the user message to be out of scope.	— not found in the data —	0
No response: There is no response to the user's repair turn	<i>Before I connect you to the medical reception team, you may find some useful info in our patient MRI guide: https://bit.ly/3qCeMQV Would you still like to speak to someone? Yes Yes Hello?</i>	4

Table 4: Bot response categorisation

Table 4 shows that the majority of user repairs lead to relevant responses which progress the conversation. However, a significant number of user repair leads to false negative responses. These initiate user repair by indicating a lack of understanding of user turns. A less frequent category are false positive responses. These are irrelevant turns which initiate repair by displaying that the user turn has been misunderstood. In a few isolated instances, user repair turns receive no response at all.

Successful and unsuccessful repair

As stated above, the main objective of his study was to investigate how users deploy conversational repair to navigate through episodes in which the bot lacks understanding of or misunderstands their intents. In the

forthcoming section, I will present, as case study, two sets of paired examples. Each of these pairs starts from a similar starting point (trouble source). In one of them, the trouble sourced was dealt with easily to allow the conversation to progress. In the other, users faced more difficulties in addressing the misunderstanding.

The first two examples start from a user question as trouble source:

Example (1)

- 1 Is an MRI scan harmful?
- 2 *Sure, what date works for you?*
- 3 I'm asking whether an MRI scan is harmful to do
- 4 *Did you mean? need *help* *thank you* clinic's *location* *None* of these*
- 5 None of these
- 6 *Sorry, I didn't quite get that. I'm still learning. Can you please rephrase the date/time you*
- 7 *provided? Thanks, Asa*
- 8 Ok fine Can I book an appointment for Thursday?
- 9 *Okay. Please choose a preferred time of day: * Morning (8am-12pm) * Afternoon (12pm-5pm) **
- 10 *Evening (5pm-8pm) * Any (8am-8pm)*

In example (1), the user asks a question about the MRI scan (l. 1), to which the bot responds with a false positive response (l. 2) which indicates misunderstanding and initiates the user's first repair. In this repair turn (l. 3), the user rephrases the original question, but does so in an 'upgraded' manner, using additional politeness features (the pre-request 'I am asking') which turn the question into an indirect question.

After the bot, in the next turn, indicates lack of understanding through a new false negative response (l. 4), the user uses one of the bot's prompts to accommodate to the bot (l. 5). When this accommodation strategy is also not successful and the bot makes another repair request (l. 6-7), the user changes the topic (l. 8) which progresses the conversation on to booking another appointment, but leaves the original question unanswered.

In example 2, a user question also forms the 'repairable', but with more immediate success in achieving repair:

Example (2)

- 1 Does it matter what clothing I wear?
- 2 *Are you trying to say? *prepare* for appointment google *calendar* link for my scheduled*
- 3 *appointment clinic's *opening times* *None* of these*
- 4 Prepare
- 5 ** You're welcome to bring a friend or a relative with you * The radiography team with explain the 6 process once you arrive * Please tell us about any special circumstances (for example, if you need*
- 7 *wheel-chair access, if you are hard of hearing, if you have poor eyesight or if you are*
- 8 *claustrophobic) Do you have any other questions or concerns about what to expect on*

Example (2) is a representative example of a successful repair within one turn. The repairable here is a user question about the preparation for the appointment (l. 1). This results in a false negative repair initiation through the bot which includes 'prompts' (l. 2-3). The user then accommodates by using one of the prompts provided (l. 4), resulting in progression to a bot turn which includes information about the

upcoming appointment. Whilst this response can be considered relevant, the information provided is only loosely related to the user's question.

The 'repairable' in the second pair of examples is user input their preferred choice for an appointment:

Example (3)

1 15/02/2022 at 2pm.

2 *It seems that your input resembles to a past date and time: 01/02/2022 14:00 PM. Please rephrase, 3 be more specific or specify a different date. Thanks, Asa*

4 15/02/2022 14:00 PM

5 *What date works for you?*

6 15/02/2022

7 *What date works for you?*

8 Admin

9 *Sorry, I didn't quite get that. I'm still learning. Can you please rephrase or try with different*

10 *date/time input? Thanks, Asa*

11 Admin

12 *Sorry, I didn't quite get that. I'm still learning. Can you please rephrase or try with different*

13 *date/time input? Thanks, Asa*

14 Reset

15 *Ok, let's start from scratch*

In example (3), the user provides a date and time input (l. 1), which is misunderstood by the bot who takes the user's choice of February 15 as being February 1st (l. 2-3). The user subsequently rephrases their turn, providing their choice in a different format (l. 4). This prompts another repair initiation by the bot (l. 5) and another attempt at completing repair by the user, this time by just providing the desired date and not the time (l. 6). After the bot's next repair initiation (l. 7), the user deploys delayed accommodation to complete repair by recycling one of the bot's earlier prompts of 'admin' (l. 8). This turn is then repeated by the user after another repair initiation (l. 11), but doesn't lead to success. It is only at this point that the user chooses a different strategy in order to move the conversation on ('reset', l. 14), which leads to progression into a new topic. This particular user is the only one who was observed to, quite literally, reset the bot in this way, so this was categories under the 'other' strategies.

Example (4)

1 I would like it to be before 3pm

2 *Did you mean? *general information* *thank you* need *help* *None* of these*

3 None of these

4 *Okay. Please choose a preferred time of day: * Morning (8am-12pm) * Afternoon (12pm-5pm) **

5 *Evening (5pm-8pm) * Any (8am-8pm)*

6 Afternoon

7 *Please select a time 13:00 14:00 15:00 16:00 None*

8 13:00 would be okay

9 Hi Akua. I'm Asa, your virtual receptionist. Happy to confirm your Screening appointment is now 10 booked for Fri 18 Mar '22 at 13:00. Is this ok?

Example 4 starts with the user making a choice about their desired appointment time. This is embedded in a longer, conventionally indirect request which includes negative politeness markers ('I would like'). After the bot's repair initiation with a false negative response that includes prompts (l. 2), the user accommodates to one of these prompts (l. 4). This leads to progression and allows the bot to offer the time-of-day selection menu (l. 4-5) and subsequently results in successful appointment booking (l. 6-10).

Success factors for repair

The four examples discussed so far have provided a first insight into the range of repair strategies deployed by users. However, they have, at this stage, not provided a clear picture as to which strategies are most likely to be successful. For example, 'accommodation' can be a successful strategy for negotiating one's way through a sequence of misunderstanding (example 4, example 2), but is not necessarily universally so (example 3).

To understand more about the success factors for working through misunderstanding, we cross-referenced users' strategy choices with the bot's subsequent responses. Table 4 shows the success ration of users' repair strategies, with 'success' being defined as a repair being responded to with a relevant response as opposed to a false negative, false positive or no response.

	relevant response	false negative	false positive	No response	Success ratio
restate purpose	8	0	0	0	100 / 0
accommodation	27	13	1	0	66 / 34
late accommodation	4	2	0	0	67 / 33
change choice	15	5	5	1	58 / 42
rephrase	22	14	6	1	51 / 49
change topic	4	3	0	1	50 / 50
question	1	3	2	0	17 / 83
repeat	1	6	1	1	11 / 89

Table 4: Bot responses after self-initiated repair

Table 4 shows that, based on this small data set, some self-repair strategies have a higher success ratio than others. The strategy with the highest overall success rate – though not one that was frequently used – was to simply restate the purpose, leading to a relevant response in every single case. Accommodation, late accommodation and changing choices also had a more than 50% success rate. Rephrasing – one of the numerically most frequently used strategies – and changing the topic were successful in approximately half of all instances, whereas simply repeating a previously used turn or asking a question were least likely to be successful.

Generally, users who are able to work through misunderstanding quickly (within one or two user turns after the repairable) – deploy those strategies which have got a higher success ratio:

Example (5)

1 Can I eat before an mri

2 Are you trying to say? *general information* *schedule* appointment *prepare* for appointment

3 *None* of these

4 Prepare for appointment

5 * The scan will be around 30 min * *Unless we let you know otherwise*, you can eat and drink as

6 normal and take any prescribed medication * You're welcome to bring a friend or a relative with
 7 you * The radiography team will explain the process once you arrive Do you have any other
 8 questions or concerns about what to expect on the day

In example (5), the user asks a question about the MRI scan (l. 1). The user reacts to the bot's repair initiation (l. 2-3) by accommodating through choosing one of the bot's prompts (l. 4). Whilst the bot's answer may not be an altogether satisfactory response to the question, it concludes this sequence and moves the conversation on.

In contrast, users who use the strategies with a lower success ratio tend to have to work harder to have their intents understood and ensure progression:

Example (6)

1 Please select a date and time for your appointment 18:00 19:00 None
 2 7pm
 3 Sorry, but I could not reschedule the appointment. Please try again a bit later, or try re-booking
 4 with different date/time. If however you are still facing issues I can connect you with someone
 5 from the clinic to help you out, just type - speak to someone. Thanks, Asa
 6 I meant 19:00
 7 Did you mean? google *calendar* link for my scheduled appointment *faq* - frequently asked
 8 questions restart *None* of these
 9 None of these
 10 Apologies, bear with me. I'm still learning. Can you rephrase?
 11 Can I reschedule
 12 No worries. Please let me know the number of the appointment you would like to reschedule: 1.
 13 Screening on Thu 09 Jun '22 at 19:00

In example (6), the trouble source is the user's input representing their desired appointment time (l. 2). The bot's response is relevant, but nevertheless initiates user repair by indicating that the desired appointment time is not available and providing a number of options for how the appointment can still be rescheduled (l. 3-5). The user completes repair by rephrasing their desired appointment time (l. 6). The user's repair is wordier than their previous version, with 'I mean' representing a personal mitigator akin to a negative politeness marker. After another comprehension request by the bot (l. 7-8), the user changes strategy and uses accommodation strategies by recycling one of the bot prompts (l. 9). When this strategy is also unsuccessful, the user's next self-repair repeats the originally rescheduling request, this time framing the request as conditionally indirect request ('Can I...') (l. 10). This third attempt at user self-repair leads to a relevant response but forces the user to restart the rescheduling conversation.

Discussion

Summary of results

The analysis presented in the previous section has showcased, through a combination of qualitative and quantitative description of user repair turn and subsequent bot follow-on turns, how users in a task-oriented chatbot use repair to work through sequences in which their intent is misinterpreted by a bot. In the subsequent discussion section, we will summarize and discuss these insights and discuss them in relation to developing communicative competence for AI.

The study has shown that the strategies the majority of all instances of repair – and thus the focus of the study – are other-initiated self-repairs of repairables in user turns. Hence, the main purpose of repair is to address issues in which the bot does not understand users’ intent – leading to false negative responses – or misunderstands it – leading to false positive answers. The study has also shown that the strategy users deploy most frequently – rephrasing – is actually one of the least successful one, leading in approximately a half of all instances to false negative answers (other repair initiations by the bot) or false positive answers (irrelevant bot responses). On the contrary, restating the purpose has a high success ration, but is only very infrequently deployed by users. In addition, ‘accommodation’ – using the bot’s own prompts – and making different choices also has a more than 50% success ratio.

This strongly suggests that users transfer strategies from face to face spoken interaction into their conversations with Asa. For example, we have shown that some users not only rephrase their original turns, but also enhance them with additional politeness markers. This mirrors strategies previously observed in face to face-interaction. For example, Kasper (2006) observed speakers that, in subsequent requests, interviewers in an oral proficiency exam treat conventionally indirect request frames as redundant, instead using the politeness marker ‘please’ to frame an overall more direct request. Plug (2014) observed that, in self-initiated self-repair, speakers engage in “prosodic marking” through higher pitch, and higher speaking tempo, and Hauser (2019) observed ‘upgraded’ self-repeated gestures in Japanese interaction. Whilst the self-repair patterns in this paper contradict rather than confer with Kasper’s (2006) observations – for instance, in some instances speakers formulate ‘repaired’ questions in a conventionally indirect manner – they nevertheless support an overall pattern of people applying learned social behaviours to their interactions (see Nass & Moon, 2000).

Whether ‘upgraded’ politeness is a matter of applying behaviours from face-to-face interaction, or is a result of other demands, remains to be further investigated by further research. In doing so, the notion of ‘pragmatic transfer’ (Kasper, 1992) which traditionally has been used to describe the transfer of L1 pragmatic strategies into an L2 and has informed plethora of research in intercultural, cross-cultural and interlanguage pragmatic since could be deployed to inform research on human-AI interaction, too.

The analysis has also revealed further insights which may have implications for users’ perceived rapport with the bot. As shown, ‘accommodation’ – defined here as convergence to the bot’s prompts in self-repair is one of the most frequently used, and one of the more successful strategies, though success is not necessarily guaranteed. Yet, such ‘upwards convergence’ towards interactional partners in superordinate positions (Giles & Ogay, 2007) may have implications for users’ perceptions of rapport with the bot for two reasons. Firstly, the conversational repair mechanisms observed here ‘role-defining’ (Liebscher & Daily-O’Cain 2003) in that they define users’ role as that of a respondent to rather than an initiator of interaction. Secondly, having to converge to receive a relevant answer in the first place, and such convergence actually often NOT leading to a relevant answer (see table 4), has the potential for implications for users’ perceptions of rapport with the bot (Spencer-Oatey, 2008). However, the exact rapport implications in user-bot interaction need to be the subject of further, more detailed investigations.

On the other hand, together with ‘restate purpose’, accommodation is the strategy that has the highest potential success rate. Yet, user awareness of this strategy and their readiness to use it, may depend on users’ overall experience with chatbots and their general knowledge of the workings of AI (Luger & Sellen, 2016). It may also depend on users’ overall orientations to these interactions: To what extent do they perceive them as ‘relational’ (relationship-oriented), or as ‘transactional’ (task-oriented) (Koester, 2004)? To what extent do they perceive of them as having human characteristics (anthropomorphism) (Hermann, 2022)?

Implications for AI skills

As discussed above, we purport here that, in order to engage with AI-driven chatbots efficiently, users need to acquire specific skills that don’t necessarily mirror those for spoken interaction. A range of models of communicative competence have previously been used to describe the competences required for social

interaction. For example, Canale & Swain (1984) describe communicative competence as consisting of four components: grammatical competence (words and rules), sociolinguistic competence (appropriateness), discourse competence (cohesion and coherence) and strategic competence (appropriate use of communicative strategies). This analysis of self-repair in user-bot interaction shows that for effective engagement in these interactions three of these competences are particularly important:

- Sociolinguistic competence: Users need to be able to be aware of the sociolinguistic environment they encounter when they interact with the bot, what this means for how they manage rapport and, consequently, how they use language. This analysis has revealed that some users may be confused about what sociolinguistic environment they are working in: they may address Asa directly or requests and ask questions with markers of negative politeness which mitigate the force of the request/question in one turn, but then accommodate to and use the bot's short prompts or restate the purpose of the interaction after an extended repair period in another.
- Discourse competence: Users need to be able to assess how the way they use language contributes to a coherent whole in user-bot interactions, and whether different ways of using language may lead to different outcomes. For example, how does the bot process and respond to a human request to form an effective question-answer pair? As the analysis of the user-bot interactions here have shown, to be effective, it is useful to know which repair strategies are likely to lead to a relevant response by the bot that shows that the user's intent has been understood and forms a coherent adjacency pair with the users' input.
- Strategic competence: Strategic competence is at the core of conversational repair as it describes the skills required for misunderstanding, and for preventing misunderstanding. As our analysis has shown, while almost none of the repair strategies mentioned has a 100% success rate, some are inherently more successful than others, and the criteria for success are different to regular face to face interaction. Our analysis has also shown that conversational flexibility may be the most important criterion for strategic competence. Conversational partners need to be able to recognise when a strategy is not successful, and then dig deep into their conversational arsenal to identify and then deploy alternative strategies.

In summary, in the same way as pragmatic competence is not necessarily developed alongside other aspects of communicative competence (Kasper & Roever, 2005), communication skills for conversational AI are not innate to all users (Luger & Sellen, 2016).

This suggests that there may be value in teaching these skills explicitly. An approach to teaching skills for effective engagement in conversational AI would benefit from including all of the elements previously described for the development of communicative competence (e.g., Jones & Stubbe, 2004 for professional communication; Dippold, 2015 for classroom interaction), such as awareness raising, experiential learning, reflection. Indeed Howard's (2012) instructional paradigm for teaching CMC skills includes all these elements, and Weisz' (2019) experimental account of teaching strategies for successful human-agent interaction does so, too. Their intervention included a phase on raising users' empathy with the bot to highlight the difficulties for dealing with user input. In this study, the instructional intervention led users to report that they had developed better strategies (e.g., use simple language, specify intent precisely). Users also developed their understanding of the algorithmic thinking process and learned to disambiguate its capabilities from human capabilities. This study is, to my knowledge, the only one currently that reports on an attempt to explicitly teach conversational AI skills. More studies which focus on AI skills 'in the wild' rather than an experimental setting would supplement this work.

AI design implications

The findings of this paper also have implications for AI design and development. For instance, in ordinary face to face interaction other-repair can be initiated by partially repeating the trouble source, often accompanied by a question word (Schegloff et al., 1977). In English as a lingua franca research, raising the explicitness of talk – described by Mauranen (2007) as 'explicitness strategy' – has consistently been observed to be an interactional strategy between speakers of different varieties of English. These also include, according to Mauranen (2006), asking specific questions, e.g., after lack of comprehension of lexical items, repetition

of problematic items in order to elicit some form of explanation. In contrast, Asa the bot initiates repair by simply indicating lack of understanding without pinpointing what was misunderstood (see, for instance, example 1). Raising the explicitness of other-initiated repair may lessen the ambiguity of repair-initiations for users. However, implications for face and rapport need further consideration as “explicitly acknowledging a mistake lowers the likability and perceived intelligence of the agent and may add friction to the interaction as the user is obliged to respond to the initiation” (Ashktorab et al., 2019, p. 3).

In addition, bot development could benefit by using user self-repair in more meaningful ways to further develop the bot’s understanding for understanding conversational intent. For example, self-initiated self-repair by users of English as a lingua franca has been described as a strategy to prevent misunderstanding by raising the explicitness of talk (Kaur, 2012). Of course, user self-repair is rarely in the open – in the data reported on above, there were only ten instances in total (see table 4, no response for illustration) – occurring more commonly when users edit their turns before they press enter. I propose that algorithms which record and learn from user self-editing might have the potential to provide insights into users’ intents. The same also applies to user self-repair after other-initiation: our data have shown sometimes extensively long sequences in which users ‘repair’ the intent multiple times. I propose that the accumulated information from these self-repairs could be used to build a more complete picture of user’ intent rather than interpreting just one user turn at a time. This proposal is supported by Li (2020) who purports that “given how hard it is (even for humans) to correctly detect the meaning of a ‘broken’ message by reading either half in isolation, we recommend that chatbot developers consider having their agents process multiple messages at a time, rather than responding so quickly” (p. 9). This would also be able to better account for the co-construction and joint mentalizing that is common to human-human interaction (Kopp & Krämer, 2021), a concept that has yet to be applied to the development of bot interactions.

Finally, the insights gained through this project also suggest that, as users are unsure about the sociolinguistic environment they are operating in, the workings of AI-driven discourse should be made clear to users. As discussed above, Weisz et al (2019) used this to teach experimental participants about the workings of machine learning algorithms to interpret intent. In practice, a short explanation at the outset of an interaction could make explicit to users the ‘rules of the game’ that appear rather opaque to many. This includes, for example, how to use the bot’s prompts, how to ‘reset’ a conversation (as in example 3). Making the rules of the game explicit to users could prevent misunderstanding before it occurs.

Finally, conversational AI systems could also be designed to recognise users’ orientations towards the discourse from participants’ own input. For example, direct forms of address directed at the bot are potentially indicative of a more anthropomorphic orientation by which users orient to the agent as humanlike (Waytz et al., 2010). Such an orientation might imbue the users with more difficulties in adapting the styles of interaction which lead to satisfactory interactional outcomes, but are less akin to face-to-face interaction (e.g., restating purpose, accommodation). Using user input to come to conclusions about their anthropomorphic or dehumanised orientations towards the bot will allow for conversations to be designed in a way to recognise users who might more support in their interactions than others.

Limitations

This study has a number of limitations. Firstly, the data analysed here were gathered as part of a methodological pilot project with a bot product that was in a ‘minimal viable product’ stage of its development. The bot responses here therefore do not necessarily reflect its full capability for dealing with user intents and initiating repair.

Finally, the data set this paper is based on is a relatively small corpus of user-bot interactions. Further research with a larger data set is necessary to further substantiate the patterns reported here. This should, ideally, also include gathering data ‘in the wild’ rather than a simulated environment. When more is at stage, users’ repair strategies may be different, e.g., for how many turns they persist in attempting repair or what strategies they choose.

Nevertheless, the analysis has provided insights which follow-up research can now further evaluate. For

instance, further research could further investigate whether and how speakers transfer pragmatic strategies from spoken interaction into bot interactions. Secondly, further research can ask how users' repair strategies relate to their expectations for rapport and their ideologies of language use. Retrospective interviews asking in detail about users' decision-making processes when interacting with chatbots have the potential to be able to tap into these questions.

In addition, it is of course also necessary to widen our gaze beyond repair. Informal observations during my analysis suggest that user success in transactional bot interactions also depends on other factors. Many of the repairables for instances were longer, discursive sentences. Are alternative formulations less likely to require repair in the first place? What do users make request (e.g., their use of politeness strategies), and how is further progress (e.g., in a booking process) contingent on its form?

In this research, this paper investigated repair strategies in a chatbot whose main purpose was 'transactional', and which fulfilled tasks such as booking and rescheduling. Further research needs to investigate the users' repair strategies in interactions with bots with a more social orientation, e.g., bots which provide mental health support or companionship.

Conclusion

Through the example of conversational repair, this paper has shown that some users are able to navigate the communication challenges posed in this environment very well, while some struggle working towards the transactional goals that the bot is meant to help them achieve. Talking with a chatbot requires a distinct skills-set, and these skills are likely to be even more complex in chatbots which use voice interaction. Further studies on the pragmatics of social interaction with chatbots will help build the "bigger picture" of what these skills are and need to be followed up with studies investigating how these skills can best be taught. Developing users' knowledge about the workings of AI will ensure that all AI users have equitable access to the everyday services bots support.

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