

Text-based dialogue structure and repair in human-computer
and human-human task-oriented interaction

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Abstract

There is currently very little research on the comparison of human-human (HHI) and human-computer interaction (HCI) in the textual modality. The aim of this study is to give an overview of the behaviour of human interlocutors when they speak to artificial intelligence agents in a text chat, and how the agents react to certain conversational norms and anomalies. I hypothesise that HHI conversations feature shorter exchanges, longer opening and closing sequences, and that human participants in HHI are able to resolve errors much more rapidly than chatbots. To investigate these hypotheses, I compared conversations in which a human spoke with an information-providing conversational agent, and conversations in which a human spoke to another human in the same information-providing role, both chat-mediated. My findings indicated that humans are able to resolve queries within a lower amount of turns, and that they require conversations to be halted much less frequently. This study fills a gap in existing research and suggests promising directions in which future study can be conducted. It stresses the importance of taking a pragmatic perspective into account when creating a conversational agent, and emphasises that using parallel HHI data to inform such development is vital to further progress in natural language processing.

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Chapter 1: Introduction

1.1 Background

The development of conversational agents which are able to understand and communicate with humans is a goal which has been long held by the natural language processing community. From Weizenbaum's (1966) robot psychotherapist, ELIZA, to the modern Siri, chatbots, "machine conversation system[s] which interact with human users via natural conversational language" (Abu Shawar & Atwell, 2005, p. 489), are now a part of our everyday life. Much analysis has been conducted on the success of conversational agents, which are typically scored by how convincingly they pass for human. Arguably, the definitive measure is the Turing test, and few chatbots have come close to passing the test.

Since its inception, research in computer-mediated communication (CMC) has addressed comparisons between CMC and other modes of communication. Ferrara, Brunner and Whittemore (1991), for instance, observe that CMC has its own unique linguistic features which bear resemblance to both written and spoken communication. Very few instances of research exist which address a comparison between human-human (HH) and human-computer (HC) interaction, as opposed to cross-modality studies, and the few that do exist typically place the focus of analysis on quantifying the more tractable linguistic features of conversation like message length, type-token ratio, and usage of emoticons (Hill, Ford, & Farreras, 2015). The development of conversational agents by taking into account ethnomethodological principles goes back to the work of Lucy Suchman (1987), whose highly influential *Plans and Situated Actions*, with its emphasis on computer supported cooperative work (CSCW) rather than human-computer interaction (HCI), was something of a starting point for the creation of more pragmatic, social, and human-like chatbots.

My research, therefore, seeks to investigate how a chatbot handles conversational norms such as the correction of errors and turn-taking. I intend to find out what similarities and differences exist between the two types of conversation, i.e., HCI and HHI, while taking into account the influence that the CMC context may hold on the interaction.

1.2 Research Question and Motivation

The present study was initially born out of an interest in the application of textual CMC. The further I delved into the literature, the more it became apparent that there is a great lack of investigation into the conversational styles people use in text chats with other people, and, much more significantly, when those text chats are held with conversational agents. It is not sufficient for chatbots to simply be assessed on their own merits. For instance, a chatbot could be able to understand a human utterance and retrieve the correct response as necessary, but if it could not make adjustments when it was corrected, or if it was not able to respond to queries and send its messages in a timely manner, then the resulting conversation would be stilted at best, and dysfunctional at worst.

It is hypothesised that:

1. HCI openings and closings are structurally less elaborate than HHI counterparts. This can be realised in the form of omitted openings and closings or as shorter sequences. HHI openings and closings have a higher incidence of topically empty turns.
2. HCI conversations feature longer sequences from an interlocutor's introduction of their query to a satisfactory resolution.
3. HHI participants are able to resolve errors such as typos more easily and can often move past them.

1.3 Structure of Dissertation

In the following chapter, I provide a brief account of Ethnomethodological Conversation Analysis (CA) and offer a review of a selection of the more significant relevant research bearing on my study. The third chapter covers the methodology used in the present study and includes a description of the datasets used and the participants recruited. Chapter 4 presents and analyses the findings of the study in a systematic fashion, using the principles discussed in Chapter 2 as guidelines. The final chapter provides an overview and discussion of the results gained in this study, and proposes ideas for future research.

Chapter 2: Literature Review

2.1 Introduction

This chapter addresses the literature that led up to the formulation of this study with an aim of providing a detailed overview of the current state of CMC research and how it relates to conversation analysis. While there exist many styles of analysis for verbal communication, delving into computer-mediated communication (CMC) is a much newer endeavour. My goal with this review is to first give an overview of the literature which has informed so much ethnomethodological research over the years, then to address the importance of redirecting our attention to modern applications. CMC is becoming more and more relevant and crucial every day, as the primary medium for communication in modern workplaces (Herring, 2011). Additionally, as conversational agents have become more commercially available, understanding the intersection of these two areas of study seems ever more pressing.

2.2 The Mechanics of Conversation

Although one may initially think that managing and participating in conversation is a simple matter which requires little consideration in our day-to-day lives, that it is “seen but unnoticed” (Garfinkel, 1967, p. 136) research concerning the mechanics of conversation would suggest otherwise. The tools employed by interlocutors in conversation are largely standardised across different instances of human conversation, collectively known as talk-in-interaction. Analysing the organisation of talk, the function of talk as a social tool, and the processes by which interlocutors instinctively know how to coordinate their talk and the content of their utterances is the domain of conversation analysis (CA). The term ‘talk-in-interaction’ specifically refers to a very wide range of forms of talk which are studied by conversation analysts (Hutchby &

Wooffitt, 2002). CA is particularly data-driven, concerned with the active representation of objects which are used to carry out the interlocutors' intentions in the talk event. In short, the primary goal of any CA-style analysis is to understand 'who said what and why' – how sentences are realised (with accounts for pauses, inflection, and duration of phonemes), how interlocutors interpret the utterances, how they react to the utterances, and all other phenomena that might become apparent in the data.

Traditionally, CA data is sourced from recorded data of naturally-occurring talk, which is then transcribed and analysed. One of the first pioneers of the CA method, Harvey Sacks, preferred this style of data-gathering because he could "study it again and again", and other researchers could repeat his investigations and form their own conclusions (Sacks, 1984). In his view, it was paramount to consider each utterance within the full context of the immediately surrounding utterances, rather than as an independent entity. One of the conversations which prompted this style of analysis is the following, from a corpus of telephone calls received by volunteers at a suicide prevention centre in Los Angeles:

Extract 1: (Sacks, 1992, vol. 1, p. 3)

- 1 A: This is Mr Smith, may I help you
- 2 B: I can't hear you.
- 3 A: This is Mr Smith
- 4 B: Smith

Sacks notices that, with a large majority, if the call receiver volunteers their name, the caller is much more likely to respond with their own. In the above instance, Sacks noticed that some callers (speaker B), unlike many others in their same position in the corpus, was not forthcoming with their name, even when the call receiver repeatedly gives his own. B seems to

misunderstand or fail to hear A's earlier utterance of his name, and upon A repeating his name for a second time, B chooses instead to confirm the name instead of offering their own. This interpretation of the exchange demonstrates the pragmatic, context-based nature of CA methodology, as the utterance "I can't hear you" does not universally represent the speaker's intention to not reveal their name but this can be inferred from the context. This idea is one of the driving forces behind conversation analysis. The principles upon which CA methodology is based were summarised by Hutchby and Wooffitt (2002, p. 23) as follows:

- Talk-in-interaction is systematically organized and deeply ordered.
- The production of talk-in-interaction is methodic.
- The analysis of talk-in-interaction should be based on naturally occurring data.
- Analysis should not initially be constrained by prior theoretical assumptions.

The systematic organisation of talk-in-interaction is analysed in multiple different features in typical CA methodology. For instance, talk can be analysed in terms of the organisation of the turns taken by the speakers in the conversation, the topics of conversation which are covered by the interlocutors, as well as the order and content of the utterances with which conversations are started and ended. I will now discuss a few of the CA principles which shall be taken into account during the analysis phase of this research.

2.2.1 The Organisation of Turn-Taking

During the course of an instance of talk-in-interaction, such as a conversation between friends, a customer trying to negotiate a price at a flea market, or a courtroom trial, the interlocutors in the conversation will naturally adopt a pattern in which they take turns to speak. As with most

other features of conversation, the organisation of turn-taking is deeply methodical and logical, and the timing is also very precise. In speech, which is the primary type of data considered by CA, as opposed to text talk, this is clearly observable in the average amount of overlapping talk generated over an instance of talk-in-interaction, reported to be around 5%, and the intervals between one turn ending and the next one starting frequently average to just a few tenths of a second (Ervin-Tripp, 1979).

Sacks, Schegloff, & Jefferson (1974) proposed a set of normative rules which can be said to govern the distribution of turns in conversation. The basic idea behind the proposition is that all available turns are shared amongst participants in the talk event, who must gain control of the floor in order to have a turn at talk. Turns are constructed from smaller turn-construction units (TCUs), at which points the turn may either end (and another speaker takes the floor or the talk ends) or continue (and the current speaker keeps talking). These points are referred to as transition-relevant points (TRPs) or transition spaces (TSes) (Liddicoat, 2011, p. 11), and here the rules of turn-taking come into play, which apply in the following order (adapted from Sacks, Schegloff, & Jefferson, 1974, p. 704):

Rule 1: applies at the first TRP of a given TCU:

- a) If the current speaker selects the next speaker, the selected speaker begins their turn when the current speaker stops.
- b) If the current speaker does not select the next speaker, any other participant can self-select and initiate their turn.
- c) If neither of these rules apply, the current speaker may or may not continue speaking by initiating a new TCU.

Rule 2: applies at all subsequent TRPs:

If Rule 1(c) applies by the current speaker, the rules are iterated through at each subsequent TRP until a change of speaker.

Within ordinary, mundane conversation, these rules are executed subconsciously by speakers within the span of just a few milliseconds, and if they are not adhered to, participants very quickly orient to the unorthodox orientation to the norms:

Extract 2: (Atkinson & Drew, 1979, p. 52)

- 1 A: Is there something bothering you or not?
- 2 (1.0)
- 3 A: Yes or no
- 4 (1.5)
- 5 A: Eh?
- 6 B: No.

For instance, in this above excerpt, speaker A repeatedly ends their turn and attempts to pass the next turn to speaker B, but B twice violates rule 1(a) by allowing a long unallocated period of silence to occur instead of beginning their turn.

However, non-mundane talk can exhibit some different features by the very nature of the environments in which this sort of talk occurs. Talk in this category incorporates work-related talk, courtroom proceedings, customer service, and, as I intend to demonstrate in this research, text-based talk. These are just some of the kinds of speech-exchange systems which are affected by the turn-taking model discussed earlier. They tend to be much more restricted, as they are governed by rules and laws external to those of talk-in-interaction. For example, cross-examination in the courtroom is restricted to two parties only, and it takes the form of a series of question-answer sequences, which heavily restricts the options speakers have at each TS (Atkinson & Drew, 1979):

Extract 3: (excerpt from Atkinson & Drew, 1979, p. 150)

- 1 C: How many climbed onto the railings thereby?
- 2 W: Very few, two or three.
- 3 C: And threw in petrol bombs?
- 4 W: Yes.
- 5 C: And then returned?
- 6 W: Yes.

The above example is comprised of three question-answer pairs. In any of the ‘answer’ turns (lines 2, 4, 6), it would likely have been inappropriate for W to provide a question, or to refrain from responding altogether (as opposed to verbally declining to respond). Similarly, in any of C’s turns, it is very unlikely that they would utter something other than a question addressed to W. In this context, talk still follows the rules – alternation between the two speakers, questions are always followed by answers – but the utterance types which form each turn are relatively predictable, and there is very little room to stray from this pattern. Schegloff (1992) uses the term ‘procedural consequentiality’ to describe the influence the context (in this case, the location of the courtroom) holds over the talk taking place in it. This example also highlights another feature of talk-in-interaction: the tendency of talk to sequence itself using adjacency pairs, an example of which is a question-answer sequence.

2.2.2 Adjacency Pairs

On a more macro level than individual turn-construction units, adjacency pairs are longer sequences in which the types of utterances are prototypical (Levinson, 1983). During talk, utterances are structured in such a way that they form logical pairs such as question-answer,

greeting-greeting, summons-answer, and many others. Adjacency pairs are crucial for the understanding of a core sociolinguistic issue: how talkers form a common understanding of the topic at hand, and how they continually reaffirm to each other that they do, in fact, understand each other, and that they wish to proceed with the talk (Schegloff & Sacks, 1973). Furthermore, as each adjacency pair is concluded (i.e. the speakers move past it without correcting the content of any utterance involved), the analyst can be sure that the speakers have cemented their mutual understanding of the talk, as no corrections to either part of the pair have been made, and the speakers are satisfied.

However, in many practical contexts, this model is not quite accurate. Much of the time, utterances are not structured neatly, and conversations are often flowing and weaving, with responses to questions potentially appearing several turns after the question that prompted them. These are referred to as insertion sequences (Schegloff, 1972, p. 76), such as this example from Levinson (1983):

Extract 4: (Levinson, 1983, p. 304)

- | | | | |
|---|----|------------------------------|--------|
| 1 | A: | May I have a bottle of Mich? | ((Q1)) |
| 2 | B: | Are you twenty one? | ((Q2)) |
| 3 | A: | No | ((A2)) |
| 4 | B: | No | ((A1)) |

The rightmost column of the above example indicates the order in which each first pair part is resolved. First, A asks B a question (Q1), expecting an answer. However, B responds with another question (Q2), which communicates to A that B is not yet prepared to answer the initial question, as B requires more information. A recognises this problem, and simply proceeds to answer Q2 instead of asking why B did not respond to Q1. Finally, once B is satisfied that they

have enough information to provide an answer, they respond in the turn 4 second pair part marked A1.

These kinds of insertion sequences can end up being quite complex, but speakers are able to naturally keep track of the exact sequence of each utterance, along with the response provided to each of them. Of course, this also means that speakers are aware of any adjacency pairs that are not completed in a satisfactory manner (e.g. a question which goes unanswered), and they are able to orient to the unnatural occurrence (Levinson, 1983). Schegloff (1972) referred to conditional relevance, which is a property that holds from first pair parts to second pair parts. The occurrence of a first pair part allows the presence of a response utterance to be relevant and explicitly recognised as a response to the first, and if the second pair part does not occur, its absence is considered significant and notable.

2.2.3 Openings, Closings, and Politeness

As noted by Schegloff and Sacks (1973), the turn-taking framework does not account for the initiation or termination of a conversational phase – the rules are recursive and, if speakers were to follow them precisely, talk would be effectively never-ending. For this, specialised types of sequences are employed when speakers wish to begin or end a conversation. They are specialised in that they often contain relatively specific content, and they can be unspecific to the topic of conversation itself. For example, utterances such as “hello” and “goodbye” are rarely used outside of the context of the start or the end of a conversation. Conversely, the specific variety of opening and closing used is, according to Schegloff (1968), much more determined by the “identity, purposes, and relationships of either or both parties.” He cites openings used by people answering intercoms, a narrow subset of phone call openings. Intercom calls are usually answered by a “yeah” or “yes”, whereas other telephone calls may

be answered with a “hello”, “how may I help you”, or “this is John speaking”, showing that the intercom context changes the way interlocutors react when receiving a call.

Openings, even those found in face-to-face conversations, are often of the “summons-answer” variety. These consist of two parts: a summons, which is invoked to call the attention of a prospective answerer, and the answer provided by the person to whom the summons was directed. As noted by Levinson (1983), summons-answer openings may be extended with a third turn, typically held by the speaker of the original summons, who would then use this third turn to give their reason for summoning the answerer, as illustrated below.

Extract 5: (Levinson, 1983, p. 310)

- | | | | |
|---|----|-------------------------|---------------------------------|
| 1 | A: | John? | ((SUMMONS)) |
| 2 | B: | Yeah? | ((ANSWER + REQUEST FOR REASON)) |
| 3 | A: | Pass the water wouldja? | ((REASON FOR SUMMONS)) |

Levinson goes on to write that the necessity of the three-part opening is generated by the question formulation in the second turn. Therefore, this turn is simultaneously a response to the summons in turn 1, as well as itself a request for a reason for the summons, which is then received in turn 3, making this three-turn sequence one that is actually made up of two adjacency pairs.

Just as openings are necessary for the creation of conversational opportunities, closings are used to allow conversations to come to a smooth end. In Schegloff and Sacks’ (1973, p. 289) words, a conversation “does not simply end, but is brought to a close”. To achieve this, interlocutors must cooperate in the closing of the conversation. Indeed, the goal of the conversational closing is to provide a “point where one speaker’s completion will not occasion another speaker’s talk, and that will not be heard as some speaker’s silence” (Schegloff & Sacks,

1973, p. 295). This is achieved using pre-closing sequences, in which one of the interlocutors indicates their desire to initiate a closing sequence. “Passes” may occur, in which the floor is passed back and forth between the interlocutors without any real topic initiation, using utterances such as “we-ell”, “OK”, and “so-oo” (Schegloff & Sacks, 1973, p. 303).

Closings can vary greatly depending on the interlocutors in the conversation. They are thought to have some significant impact on the relationship between interlocutors, as implied by Bardovi-Harlig, Hartford, Mahan-Taylor, Morgan, & Reynolds (1991). They reference a conversation in which one interlocutor responds perfectly to the other speaker’s attempt to say ‘goodbye’, but fails to follow through in a timely manner, resulting in the interlocutor needing to be ushered to the door. This implies that closing sequences, as well as openings, may have a significant impact on the perceived character of the interlocutors conducting the conversation. The manner in which openings and closings are conducted, and, indeed, if they are used at all, can reveal a lot about the level of politeness that interlocutors wish to employ.

2.2.4 Repair

On the topic of conversation flowing smoothly, built-in mechanics allow talk to account and adjust for mistakes, misunderstandings, and other ‘blips’ in the system. The procedure of repair is employed “in response to a linguistic problem, such as the inability to retrieve lexical items, and the incorrect use of pronunciation, lexis, or syntax” (Pillai, 2006, p. 114). It is worth noting that ‘repair’ does not necessarily refer to interlocutors making speech errors, but, more generally, to ‘corrections’. These include instances in which an interlocutor simply misspeaks or uses one word when they meant to use another. Repair may also occur when a speaker says something that they believe to be true, which is then corrected by another speaker. The original error is known as the trouble source, and it is from this point that the turns which contain the

repair procedure are initiated. Any speaker can produce a trouble source, initiate a repair, and carry out the repair itself (Hutchby & Wooffitt, 2002).

There are four types of repair as discussed by Sacks, Schegloff and Jefferson (1977), with brief examples made up by myself:

1. Self-initiated self-repair: Repair is initiated and carried out by the original producer of the trouble source.

A: 'Go towards the left – ah, no, the right – of the tree.'

2. Self-initiated other-repair: Repair is initiated by the original producer of the trouble source, but carried out by another speaker in the conversation.

A: 'I think it was Matt – no, maybe it was...'

B: 'It was Peter!'

3. Other-initiated self-repair: Repair is initiated by another speaker, but the person who caused the trouble source also carries out the repair action.

A: 'I was talking to Ben—'

B: 'Are you sure?'

A: 'Ah, no, come to think of it, it was John.'

4. Other-initiated other-repair: Repair is both initiated and carried out by a different speaker to the one who produced the trouble source.

A: 'Did you hear? Mike got a new green car last week.'

B: 'No, he was going to get the green one, but he ended up picking blue instead.'

Repair may be initiated at any point after the trouble source is produced, up to a certain limit, which is generally measured in the amount of turns between the trouble source and the repair action itself. In the first position, the trouble source, repair initiation, and repair execution all occur within the same turn, as in Example 1. Repair in the second position occurs one turn

away from the trouble source, and therefore refers to other-repair, such as in Examples 2 and 4. Repair in the third position is two turns away from the trouble source turn, as in Example 3, in which the repair is initiated by another speaker, then resolved by A in the next available turn. It would be highly unlikely for a repair sequence to be found more than four turns away from the trouble source, such repair as only occurring when it becomes “next relevant” (Schegloff, 1992, p. 1325). Schegloff (1992) described this repair as the “last structurally provided defense of intersubjectivity in conversation” (p. 1304). In short, repair that is executed in the third and fourth position is essentially the speakers’ ‘last chance’ at resolving a trouble source. It is this establishment of intersubjectivity which necessitates the existence of repair as a conversational structure.

2.3 Mapping Conversation Analysis to Textual Dialogue

2.3.1 Introduction

Traditionally, conversation analysis has been heavily restricted to spoken conversation, owing to the original data collection practices employed by pioneers of CA research. Simultaneously, most analysis of text is typically reserved for non-interactive settings. Despite the limitation of a lack of existing research in textual CA, some researchers have attempted to move forward with applying discourse analytic techniques to this new textual medium. Prior research into the comparison between human-human and human-computer interaction has focused on linguistic features such as utterance length and usage of shorthand (Hill, Ford, & Farreras, 2015). The research presented in this dissertation aims to compare the same two types of interaction from a pragmatic point of view in the context of information-seeking transactions, which will be able to give a starting-off point to future research.

The analysis of textual dialogue falls within the area of computer-mediated communication (CMC). Textual CMC is becoming more and more relevant as a “prime site for conversation”, replacing spoken conversation in many instances of professional and personal interaction (Herring, 2011). While much textual analysis discusses the medium as an independent structure in its own right, that is to say, with its own conventions and patterns, in the case of communicative text, it is vital to consider textual conversations to be equivalent to and inspired by spoken conversations, albeit with their own adaptations and limitations as a result of the medium. Herring writes that “Internet users often refer to textual exchanges as conversations, using verbs such as ‘talked,’ ‘said,’ and ‘heard’ rather than ‘typed,’ ‘wrote,’ or ‘read’” (Herring, 2011).

Important distinctions between text and spoken communication must be taken into account when analysing textual conversations. The most obvious difference is that fact that, as a written medium, each message sent by interlocutors is re-readable and easily accessible. Interactants are able to refer back to old sections of the conversation with full accuracy, allowing them to maintain a certain degree of accountability amongst each other (Giles, Stommel, Paulus, Lester, & Reed, 2015). This feature of textual conversations is likely to have an impact on those conversational features which rely on the availability of past utterances, such as repair.

Other distinctions are more related to the natural differences which exist between typed and spoken utterances. For instance, a lot of the ‘preparation’ for an utterance is hidden to interlocutors in chat conversations, whereas if a speaker were to attempt to prepare an utterance, their hesitation, restarts, or instances of self-repair would be clearly displayed. One way in which developers of chat software have attempted to bring text conversations closer to their more standard spoken counterparts is the addition of small icons that indicate that somebody in the conversation is typing. Ergo, if user A begins to type a message, deletes it, then restarts, user B would correspondingly see a ‘typing’ icon appear in the window, disappear, then reappear. However, this naturally gives no information as to the content of the potential messages, unlike a verbal restart or self-repair, in which the intended content of the utterance can often be guessed.

2.3.2 Repair in CMC

Meredith and Stokoe (2014) distinguish between two types of repair which may apply to text chat conversations. The first is visible repair, which is visible to all participants in the conversation, and can therefore be oriented to. The second is message construction repair, which is, as mentioned earlier, the type in which one interactant takes time to revise their reply

before sending it. The existence of this second type of repair “shows how participants in written interaction are oriented to the same basic contingencies as they are in spoken talk: building sequentially organized courses of action and maintaining intersubjectivity” (p. 2).

Message construction repair represents an essential difference between spoken and text conversations: turn construction and turn transmission do not occur at the same time. While some textual communication like email and forum exchanges can be considered to be asynchronous, as responses can be delayed by hours or days, faster methods of textual communication are said to be quasi-synchronous (Garcia & Jacobs, 1999). Additionally, Garcia and Jacobs note that, as messages are constructed in their entirety before being sent to a recipient, interlocutors cannot predict likely transition spaces at which they might be able to interject with their own turn. Therefore, much talk occurs simultaneously, with messages being sent and received without waiting for an empty turn. This does not necessarily pose a problem, as the persistence of text messages allows for interactants to review messages long after they have been sent, rather than expecting an immediate response, as one would normally expect with an oral conversation. This pattern is documented by Nelimarkka, Lehtinen, Ukkonun, Kuikkaniemi, & Jacucci (2015), whose study revealed that chat conversation unfolds itself naturally into ‘threads’, and that participants are able to keep track of simultaneous conversations in a singular chat instance.

Returning to the prevalence of repair in textual conversations, Meredith and Stokoe’s (2014) work revealed an important characteristic. They suggest that similar features of message construction are oriented to with repair events in online communication as in ordinary talk, including “repairs on stance, prosody, and action formation” (p. 48), indicating that, like in spoken interaction, textual communication still keeps to the same principles and norms which govern social interaction, using repair to maintain intersubjectivity. They also find that the

preference for self-correction still holds in online communication, as discussed for spoken interaction by Schegloff *et al.* (1977).

Schönfeldt and Golato (2003) investigate positions at which repair can occur in chat conversations. Their findings demonstrate that participants adjust their practices to the specific nature of the chat itself, reflecting Meredith and Stokoe's (2014) assertion that online communication is its own speech-exchange system which heavily takes cues from spoken conversation. Due to the nature of turn-taking organisation in online communication, repair can be initiated at various points in the conversation following a trouble source. A repair type they identify is Next Opportunity Space Repair. As messages are composed away from the view of other participants in the chat, an interactant can send off a message, begin composing a new rephrasing of the same message, but another participant sends their own message while the first is typing. Hence, when the first participant finishes and sends their message, representing a repair action, this will appear in the next opportunity space in the chat (Schönfeldt & Golato, 2003). Their findings also support the similarity between textual chat conversations and spoken interaction. Like Schegloff *et al.* (1977), they find that self-repair is still preferred, as well as that when encountering a trouble source and initiating repair, the conversation halts until the repair is complete.

2.3.3 Turn-taking and conversational structure

As noted earlier, the turn-taking structure of oral conversation often takes the shape of one speaker at a time, with some minor overlap in places. However, the quasi-synchronous nature of textual dialogue means that multiple participants in a conversation are able to send messages simultaneously, without waiting for the 'speaker' to finish before taking a new turn (Garcia & Jacobs, 1999). Therefore, the medium itself shapes the turn-taking patterns that are established

throughout a conversation (Garcia & Jacobs, 1999; Schönfeldt & Golato, 2003). As noted by Nelimarkka *et al.* (2015), speakers are easily able to keep up with various ‘threads’ of conversation at once, and orienting to trouble sources at a later stage is unlikely to be a problem. Markman (2005), Meredith & Stokoe (2014), and Garcia & Jacobs (1999) reiterate the fact that each turn is essentially composed privately, and only a final product is visible to other people in the conversation. While participants can compose their messages at their leisure, it remains possible that if they were to take too much time in composing their message, they risk the topic changing and their unsent message becoming irrelevant (Markman, 2005).

The allocation of turn space in a CMC environment is also found to be relatively different to that in oral conversation, while the turn pattern of the interaction itself remains similar to the traditional Sacks *et al.* (1974) model. Garcia & Jacobs (1999) view it as a systematic disabling of features of the model. Overlap is one kind of conversational problem which must be resolved, which can be summarised as the commencement of a turn while another turn is still ongoing, or the simultaneous self-selection of two or more speakers (Jefferson, 2004). When overlap occurs outside of a TRP, it is often considered an interruption, and is often oriented to by the holder of the current turn. In textual CMC conversation, the idea of ‘overlap’ applies in a much less significant manner, as the transmission of one complete message (turn) cannot interrupt the formation of another (Anderson, Beard, & Walther, 2010). Participants do not orient to out-of-turn utterances as ill-intentioned, as the sending of an overlapping turn does not prevent them from carrying out their intended turn. Rather than being a hindrance, overlap instead allows participants to be more productive than they would otherwise be in a face-to-face scenario, as was found by Anderson *et al.* (2010).

The way overlap and turn organisation pan out in textual CMC has a significant impact on the overall structure of conversation, such as the patterns of turn adjacency. In the spoken modality, one would follow a single thread of conversation by passing from one turn to another according

to the Sacks *et al.* (1974) turn-taking model. However, as text messages remain visible and reviewable to all participants in the conversation, multiple threads are allowed to coexist, so participants often have to manually identify which messages go together (Herring, 1999). As a consequence, turn adjacency may be disrupted. Meredith (2017) finds that interactants rarely orient to icons which indicate that somebody in the conversation is actively typing, rather than using them to avoid potential overlap. Her participants often write messages at the same time, which are then sent at very similar timestamps, and subsequently responded to individually. In one example, a participant sends a message to the chat window, but receives an entirely unrelated message from the person they are communicating with. The second person continues along their own topic rather than choosing to respond to the message from the first. Some interactants also prefer to transmit and respond to messages in a list format, in which they send multiple messages, and it can be easily assumed that, should they receive a similar list format of messages back, each answer corresponds to a message respectively (Meredith, 2017).

2.3.4 Impact of setting on conversations

It has been demonstrated by researchers (Anderson, Beard, & Walther, 2010; Meredith, 2017; Meredith & Stokoe, 2014) that the setting in which an interaction takes place is much more relevant to CMC than to spoken communication. In spoken CA, the setting of an interaction is taken to be irrelevant up until the point where the participants orient to it (Heritage, 2004). Instead, Meredith (2017) discusses ‘affordances’, which refer to the possibilities that an object may offer for action. She draws on the work of Hutchby (2001), who used the concept of affordances to demonstrate the way social interactions orient to the technological setting. Using Facebook chat as a medium for her analysis, she cites affordances such as the small icon that appears in the window when somebody in the conversation is constructing a message, and the

persistence of text messages which allow users to respond several turns after the original message. In this sense, the technology both affords the ability for interlocutors to write at the same time, but allows them the option of waiting by informing them that a message is on the way. Another affordance available to users is the ability to delay their response. For instance, Facebook chat provides a marker to tell friends that a person is online, but this does not mean they are actively sitting at their computer, nor are they necessarily willing to converse. They may receive a message, note that the message is waiting to be read, and choose not to respond at that moment. Anderson *et al.* (2010) use a relatively unique CMC system which displays how interlocutors orient to changes in the system which might be new to them. The VAX Phone system displays both sides' utterances as they are being typed, such that the message construction phase of the turn-taking system is visible to other interlocutors. Consequently, participants in their study performed a relatively small amount of interruption, instead producing much smoother turn transitions than even spoken interaction would allow for.

While spoken and face-to-face conversation allow interlocutors to latch onto features such as tone, prosody, facial expressions and gestures, these are not present in text-only chat. This is where features of individual chat services may come into play, with the presence of emoticons to convey the hidden emotion that would normally be revealed by, say, the facial expression of disappointment (Goutsos, 2005). Some services include the possibility of voice communication, as well as the addition of a webcam option, so speakers can show their face to their interlocutors. To convey stress markings and emphasis, many services such as Facebook chat allow users to bold their text by surrounding it with asterisks (Meredith & Stokoe, 2014).

On a more technical level, one must keep in mind that CMC relies on the technological medium in use. Ergo, it suffers from potential technological shortcomings, such as a slow network speed, server delays, or a lack of connection. This may result in messages being delivered much later than intended, which could also result in disrupted turn adjacency.

2.4 Fantastic Machines and How to Talk to Them

2.4.1 The Inner Workings of a Chatbot

In a world which is moving towards the automation of as many tasks as possible, it should not come as a surprise that one of the ultimate goals in natural language processing is the creation of software that is fully capable of producing and understanding human language. Conversational agents, or chatbots, are artificial intelligence systems designed to simulate natural language in order to communicate with humans for various tasks, often using speech rather than text (Jurafsky & Martin, 2009). Common use cases for such agents include travel agents, information seeking services, and personal assistants. From the early days of ELIZA (Weizenbaum, 1966) to modern chatbots which live in devices in the palms of our hands, the development of conversational agents has made huge strides towards a realistic representation of natural language.

Dialogue systems take cues from human dialogue to understand utterances being said to them, as well as to respond with the correct language in turn (Woodruff & Aoki, 2004). Since the work of Lucy Suchman (1987) on computer supported cooperative work (CSCW), dialogue system designers have taken into account CA principles to create their chatbots with a more user-oriented perspective. Conversational agents are designed to follow turn-taking rules (an agent will try not to interrupt a human user), observe correct responses to questions (agents are programmed to produce an answer when faced with a question), and seek information that is lacking, using their own form of repair. In addition to conversation structure, conversational agents should also have an awareness of some of the nuances that come with natural language that might not be immediately obvious in the meaning of the words themselves. For instance,

dialogue systems should be able to parse instances of lexical or syntactic ambiguity, so that indirect utterances and conversational implicature can be resolved accurately.

Dialogue systems are generally composed of six primary components. First, the speech recognition component translates the speech into understandable text, which is then converted into more machine-readable meaning by the natural language understanding (NLU) component. This request is fed to the dialogue manager, which interprets precisely what information must be retrieved from the task manager component. Once the system has an answer for the user, it is passed back to the natural language generation (NLG) component, which translates it into human-friendly text, which is then verbally read out by a speech synthesis system.

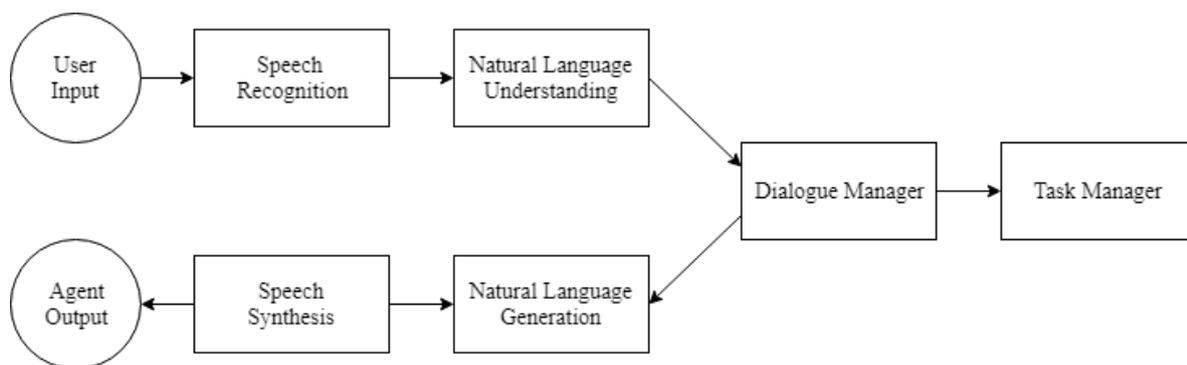


Figure 1: System Architecture. (Adapted from Jurafsky & Martin (2009)).

The dialogue manager is the backbone of the system, and can be built in different ways depending on the usage of the system. One type is a retrieval-based model, in which the chatbot has a finite bank of responses from where it can pull an appropriate answer based on the type of answer needed and the context of the rest of the conversation. These responses are hard-coded into the database, and often take the form of templates into which variables can be inserted (Huang, Zhou, & Yang, 2007). The disadvantages of such approaches are the amount of man hours required to build up the database, which must be done manually for each domain, and a limitation in the variety of responses. Databases can be built up automatically from various sources, such as corpora in the relevant domain (Abu Shawar & Atwell, 2005) or online

discussion forums (Huang et al., 2007). For a more sophisticated system which can handle a wider variety of inputs, generative models can be implemented which use statistical machine learning techniques such as Markov models to develop a deeper memory bank of responses (Surmenok, 2016).

High-quality conversational agents are able to handle errors and interruptions smoothly. Ross (2012) discusses error handling that provides an appropriate response that acknowledges the error and requests a second try from the user. Other approaches (Jurafsky & Martin, 2009; Cohen & Hunter, 2004) involve the agent confirming its understanding of the user's utterance, which can either be done explicitly (directly repeating the user's request as a question) or implicitly (asking a subsequent question which includes the prior information, which the user may then correct). If the program is unable to resolve the user's utterances to logical meaning that it can interpret, it can produce a response such as "I'm sorry, I didn't understand that", implicitly asking the user to reword their request (Jurafsky & Martin, 2009). This error handling is a way in which repair actions are implemented in conversational agent systems.

2.4.2 Applications for Conversational Agents

The first chatbot made available to the world was the robot psychologist ELIZA (Weizenbaum, 1966). Named after the protagonist of George Bernard Shaw's *Pygmalion*, it was designed to incrementally improve its behaviour the more it interacted with 'patients'. It sourced responses from a database based on keywords extracted from user input utterances. Nowadays, chatbots have become much more commercially available, with every smartphone and most personal computers sold coming with one of the four major products: Apple's Siri, Microsoft's Cortana, Google's Google Assistant, and Amazon's Alexa. People can ask about the weather,

automatically add new appointments and tasks into their calendar application, and send text messages by simply speaking instructions at the agent.

Chatbots have also been integrated into industry, with popular usage including customer service (Xu, Liu, Guo, Sinha, & Akkiraju, 2017), facilitating and assisting learning in education (Tegos, Demetriadis, & Karakostas, 2017; Heller, Procter, Mah, Jewell, & Cheung, 2005), and tourism (D'Haro, et al., 2015). Such applications allow productivity to increase in workplaces, and allow human agents to focus on potentially more important matters. Whereas a human can physically only handle one query at a time, a chatbot is able to deal with many more customers at once. The addition of machine learning as opposed to simple templates and canned answers gives a relatively cheap personal touch to automated customer service (Button, Coulter, Lee, & Sharrock, 1995). Often, the artificial intelligence system is able to handle a query single-handedly, but may still redirect the query to a human who is more able to deal with unspecific language and new queries which the bot might never have encountered (Jurafsky & Martin, 2009).

The perception of chatbots is ever-improving due to the wide availability of programs like Siri and Google Assistant. Candela (2018) found that the primary reason for chatbot usage is productivity, with 54% of people surveyed citing that reason, followed by 29% of respondents citing curiosity. Userlike, a company which sells a simple chatbot and live chat software to companies for human support teams, conducted a survey with 100 respondents (Userlike, 2019). They found that the majority of respondents preferred to instantly connect with a conversational agent when seeking customer support, rather than waiting for a human to be available. Additionally, respondents prefer to have the chatbot make it clear that it is not human, but simultaneously wish for the chatbot to display some human qualities, such as a sense of humour. Clearly, therefore, the primary preference for chatbot functionality is usefulness, rather than entertainment. Efforts have been made to make chatbots have more human-like conversations,

while ensuring that they still remain clearly artificial. Cassell and colleagues' work on embodied conversational agents aims to synchronise the dialogue of an agent with a three-dimensional animation which is capable of making gestures and facial expressions (Cassell, Bickmore, Campbell, Vilhjálmsón, & Yan, 2000). Ciechanowski, Przegalinska, Magnuski, & Gloor (2019) showed that chatbot users prefer simpler text-based chatbots, rather than complex, animated systems, which tended to give users the 'uncanny valley' effect, where the more complex the system, the more uneasy and uncomfortable they felt. Nevertheless, one of the most well-known non-commercial chatbots for casual conversation is Cleverbot, which has been learning from human interlocutors since 1988 (Carpenter, n.d.).

It is, therefore, in light of these considerations that the methodology presented in the following chapter has been developed. The approach taken by Hill et al. (2015) of comparing datasets for each type of interaction is particularly relevant to the qualitative nature of the analysis underlying my study. By systematically comparing conversational features such as turn-taking, openings, closings, and repair, I intend to further explore the human perception of conversational agents and to examine human speech in the context of chatbot conversation.

Chapter 3: Methodology

3.1 Structure

The present research was carried out in two parts. As previously discussed in Chapter 1, the analysis took the form of a comparison between two types of data: textual conversations in which one participant is a human agent and the second participant is a chatbot (hereafter, HCI conversations), and conversations in which both participants are human agents (hereafter, HHI conversations).

The focus of the analysis presented here was the specific conversational nuances that may arise as a consequence of a human participant speaking to an artificial intelligence chatbot as opposed to a fellow human being. These include:

- the treatment of trouble sources when they arise
- turn-taking procedures
- length, utterance types, and any politeness terms used during openings and closings
- addressing of unexpected and unconventional orientation to the norms

To eliminate biases and variables that may arise from the inclusion of additional participants, all conversations studied were restricted to two participants at any given time. The analysis took a qualitative form, as the primary focus of this research is a direct comparison between the conversational norms of HCI and HHI.

3.2 Phase 1a: HCI Data Collection

Collection of HCI data was carried out with the cooperation of a Maltese company, ebo. The company operates a commercial chatbot which is customised to meet client requirements,

including the addition of a knowledge base specialised to the domain. The particular variation of the chatbot that is created for any given customer is often designed to replace human customer support agents within the company, increasing the speed of the company's workflow.

The particular domain of HCI data that will be collected comprises queries about the European Union's General Data Protection Regulation (GDPR), an European Union (EU) law enacted on May 25th, 2018, which has caused every website available to EU countries to warn users of potential data collection, which, in turn, has prompted questions from users who may not understand what the GDPR means. This is where ebo comes in: a chatbot that can answer most general questions about the GDPR and its implications on the average person. In this particular implementation, ebo is named Oliver, and it is an expert on GDPR and translating the GDPR into layman-friendly language.

The format taken by Oliver is a simple question-answering system, with the assistance of button input in case users are unable to formulate a question Oliver can understand. The button input options are used as an alternative to manual text input, and are displayed as part of some of Oliver's messages (see Figure 2, where the buttons are shown in the third message). The impact of these buttons on the conversation is addressed in Chapter 4, section 4.2, together with a more detailed account of why they are implemented in the first place. The display encountered by users of the chatbot is shown in Figure 2. Following some introductory messages in which Oliver explains, users can freely type in the text field provided or they can select one of the predetermined buttons to automatically give it as input.

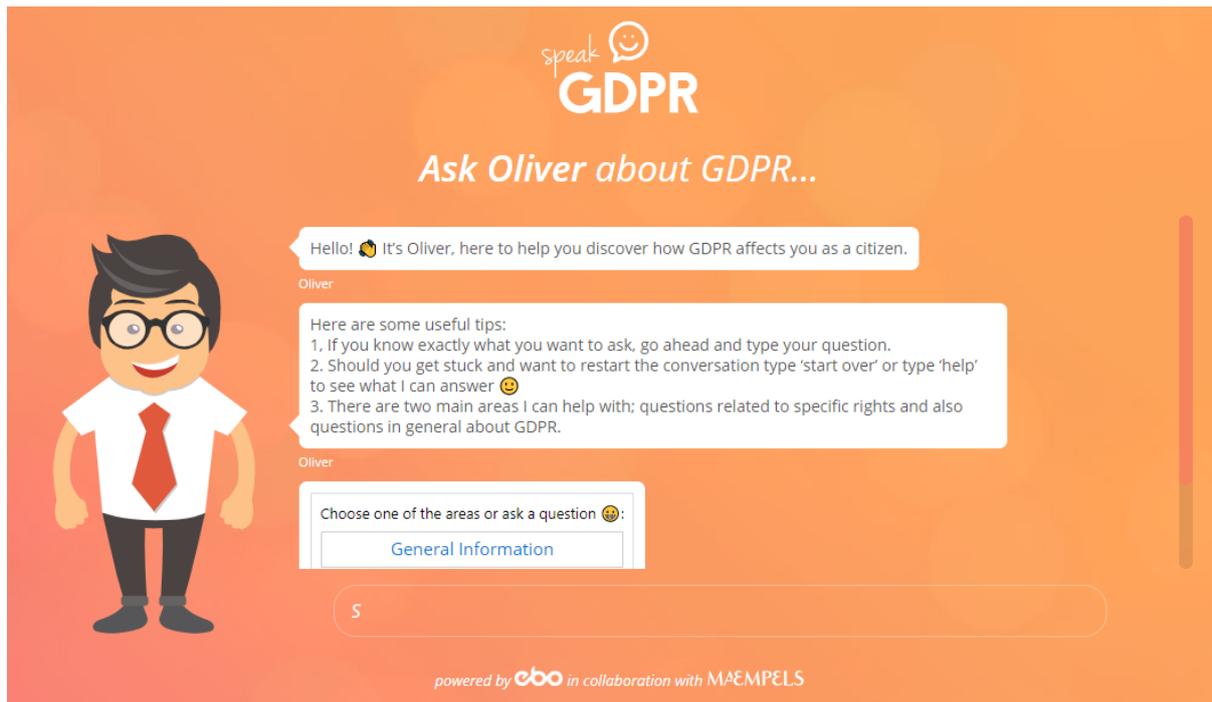


Figure 2: The Oliver interface

The principle reasons for selecting this method of data collection for HCI data were availability and access. The availability of a chatbot owned by a local company enabled easier access to the data and ensured a wide spread of participants from around the country.

Naturally, information about participant demographics is not readily available. As discussed previously in Chapter 2, section 2.4.2, chatbots are primarily engaged by users who either wish to stay anonymous or would prefer a fast response to their query (Userlike, 2019). All data was collected anonymously and conversations were typically short and to-the-point. These points ensured that the HCI data collected was as authentic as possible to the real ‘chatbot experience’ present in industry.

The HCI data was collected and anonymised by an employee at ebo and organised into four sets of transcripts, with each conversation given a number. Each conversation was presented in a format that clearly designated which lines belonged to which speaker by aligning human messages to the left and chatbot responses to the right, shown in the excerpt below:

Extract 6: (ebo ltd., 2018, transcript 1)

- 1 what is GDPR?
- 2 The name makes it sound more difficult than it really is. In simple terms, GDPR is the new official law issued by the European Union that applies all across the EU

The first phase of analysis was the annotation of the HCI transcripts, initially by labelling instances in which the human participant used the button inputs. Then, instances in which the human participants attempted to formulate sentences that the chatbot might understand, and cases in which they were both successful and unsuccessful in eliciting a suitable response from the chatbot.

The conversations were also analysed to obtain a list of response types that both the human and chatbot frequently used, in order to create a list of prompts to be given to participants in the HHI data-gathering sessions, described below.

3.3 Phase 1b: HHI Data Collection

In order to create a parallel dataset of HHI conversations, information was taken from the HCI dataset to create helper prompts. This was done to keep the two datasets in relatively similar domains, in an attempt to reduce the likelihood of differences between the two genre types arising out of genre incompatibility. Additionally, as no demographic data is available for the HCI dataset, the participants used for the HHI data were sourced randomly from social media.

Participants were then split up into pairs randomly and asked to hold text conversations with each other. These conversations were not mediated for duration, as limiting the amount of time available to participants might influence the sequence length of certain operations such as openings and closings, which are two of the data points which will be analysed. Instead,

participants were given a list of prompts which they could choose to include in their conversation (see Appendix B for a list of prompts). Participants were told to conduct their conversations freely as they saw fit. In each of these conversations, one participant was assigned the role of ‘agent’, paralleling the chatbot role in the HCI dataset, while the other participant was assigned the role of ‘client’. Those in the agent role were told that their prompts may or may not be used, whereas when in the client role, they were requested to use at least three of the prompts given.

The conversations took place using Vsee, a chat application which does not include features such as emoticons. It is commercially available for free download and is intended for remote doctor-patient appointments, which affords it a minimalistic design. None of the participants had used the software in the past. Contrary to the Oliver chatbot interface, this software does not include button inputs to prompt user responses. It is likely that

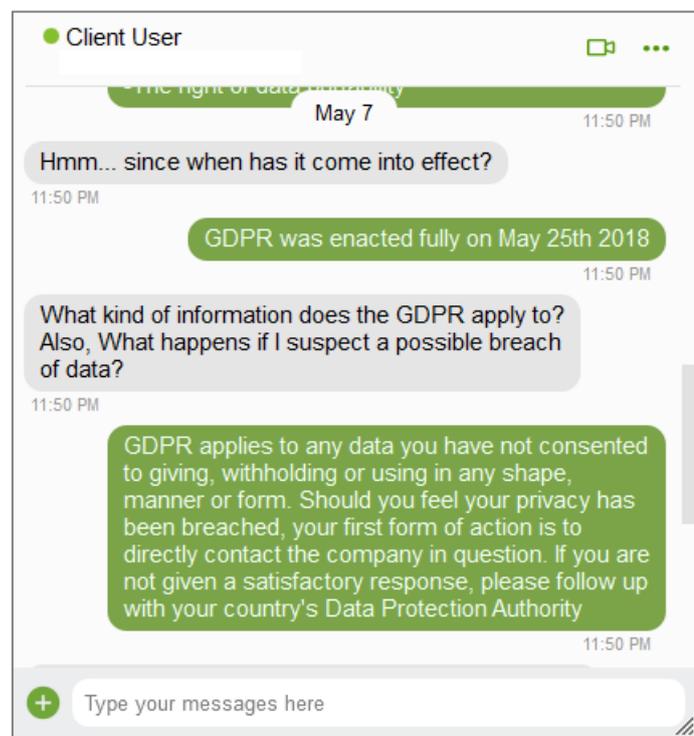


Figure 3: The Vsee interface

the absence of buttons may have had some influence on conversational flow in the HHI participants' interactions (see Chapter 4, section 4.2 for a discussion).

3.4 Phase 2: Using the analysis to inform an improved agent

Following the analysis, a list of improvements to the chatbot was derived and used to inform a simple chatbot I wrote, named Toby (see Appendix D for Python code). Some of these improvements were implemented, such as a simple spellchecker, which was sourced from the Python package `Spellchecker`. `Spellchecker` has a built-in frequency list of common words, which it uses to determine if words are misspelled and their most likely correction. Additionally, I added a check for profanity, as Oliver displayed some inaccuracy in dealing with occurrences of such language (see section 4.5.2 for more details). Like Oliver, Toby uses a keyword system, which prompts a certain response if it detects the presence of a keyword in the user's utterance. Toby allows users to exit the conversation at any point by typing the word 'No', and, unlike Oliver, gives the possibility of users responding to greetings as they are displayed.

In the next chapter, I present some observations from my analysis, as well as a discussion regarding the impact of the button inputs on conversation. I also discuss some of the characteristics exhibited by the conversational agent which will partially inform my analysis, particularly with regards to understanding the reason behind some of Oliver's actions. Finally, a list of potential improvements to Oliver was developed, taking into account some unsatisfactory responses given by Oliver, and how similar questions were handled by human participants.

Chapter 4: Results and Analysis

4.1 General Information

In total, 72 HCI conversations were collected. The data was sourced from the local company ebo, which launched a chatbot named Oliver. Oliver's task is to answer questions about the European Union's General Data Protection Regulation (GDPR) and assuage any concerns that the layperson may have about their online security. As discussed in Chapter 3, section 3.2, demographic data and linguistic background was not available for the participants in these conversations. Information and access to the chatbot were made available in late 2018 via media articles paid for by the company. Out of these 72 conversations, the longest conversation length was 72 turns, with two conversations having that length, and the shortest was 6 turns.

20 HHI conversations were collected from 20 participants. 20 participants were selected due to time limitations, and each participant carried out a conversation from both the agent and client role. This was done in order to avoid potential biases arising from a single participant reprising the same role more than once. The participants were sourced from random respondents on social media, as well as word of mouth recommendations from colleagues and friends. No HHI conversations were removed from the dataset, as I requested that the client in each conversation use at least three prompts (see Appendix B for the full list of prompts), which ensured conversation lengths of at least six turns (the three prompts, and at least one turn in response to each). The longest conversation length was 18 turns, and the shortest was 9 turns.

4.2 Button Inputs

After Oliver sends all planned messages, he often will end his turn by providing some button inputs which users can click. The text in the buttons is automatically submitted as the user's turn, optionally replacing their ability to type out a custom message. The impact that these buttons have

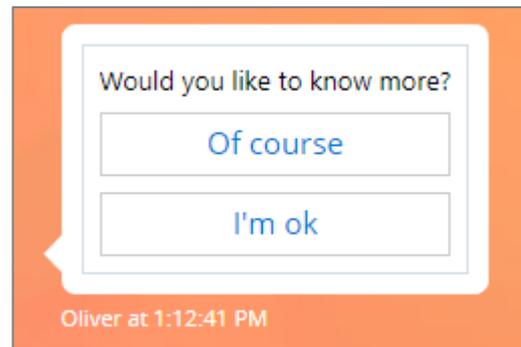


Figure 4: The button inputs offered by Oliver

on the conversation is quite significant. The first conclusion that can be drawn is that the buttons are included to guarantee that the user provides an input that Oliver is able to respond to. They eliminate the possibility of unfamiliar keywords and unknown phrases, which might cause Oliver to respond with unsatisfactory messages like "Sorry, I didn't understand that". Naturally, users expect a coherent answer which links to the question they asked or prompt they selected, and in an ideal scenario, the bot would be able to provide a response to every message. The presence of button inputs ensures this outcome, albeit at the cost of customisability.

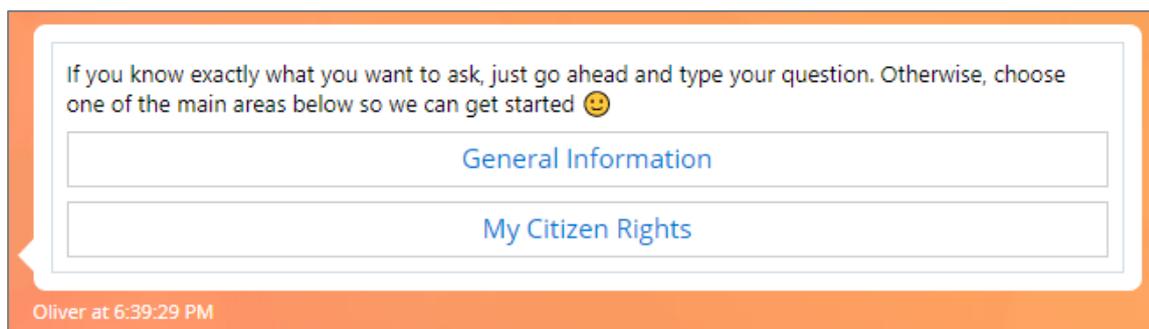


Figure 5: Oliver's first button input offering

Oliver actively encourages the client to use the button input options. Pictured above is the last message in Oliver's initial greeting (Fig. 4). He asks the user to type their query into the

provided chat box at first, but lets them know that selecting a button choice is an alternative. Out of 72 conversations, 44 of them were initiated from the user's side by one of the two buttons presented above. In general, these conversations seem to proceed more successfully than those in which the client's first utterance is a custom typed one. For instance, Extract 7 is an example of an unsuccessful attempt by the client at engaging with Oliver using the chat box.

Extract 7:

- 1 Client: whos fault is gdpr
- 2 Oliver: Sorry, I didn't understand that
- 3 Client: what country introduced the GDPR
- 4 Oliver: I'm not sure what you are asking :(
- 5 Client: What dods GDPR stand for
- 6 Oliver: I don't understand sorry. Try asking "help" to see what I can do...

In each of its turns, Oliver expresses a lack of understanding and implicitly attempts to prompt a new response from the user, even though the client message in turn 3 was not excessively mistyped and only lacked punctuation and a starting capital letter. In other instances, Oliver displays understanding of messages which, similarly, lack correct grammatical formation.

Another function of the button inputs is the control they offer over the conversational topics. They encourage client users to stay within the limitations of Oliver's knowledge base, which may not be able to account for more specialised questions. In this instance, a user attempts to ask a custom question in the chat box, but Oliver is unable to parse it:

Extract 8:

- 1 Client: When can the data be passed directly to my new provider
- 2 Oliver: Type 'yes' if you have another question or 'no' if you're done

- 3 Client: yes
- 4 Oliver: That's what I like to hear. What is it that you would like to know?
- 5 Client: when can the data be passed directly to my new provider?
- 6 Oliver: I'm not sure what you are asking :(

Oliver also occasionally uses an alternative to the button input system which has the same intentions. The chatbot will suggest a list of questions for the user to ask, with the intention of having the user precisely repeat the same wording. In Extract 9, Oliver gives some questions, and is unable to understand one of the questions presented with modified wording.

Extract 9:

- 1 Oliver: Glad to help! Go ahead and ask a question, but if you are unsure of what to ask, here are some examples:
- 2 Oliver: How does GDPR affect me? What is new in GDPR? What are my rights according to GDPR?
- 3 Client: how does it affect me?
- 4 Oliver: I'm sorry, I don't know how you do that
- 5 Client: How does GDPR affect me?

Oliver is here unable to resolve the pronoun 'it' to 'GDPR', which causes it to provide an unsuccessful response to the question. After the user repeats the question as intended by Oliver, it is able to give the correct response following this extract. This demonstrates one of the limitations of this particular chatbot: it is unable to go beyond the scope which was specifically programmed into the system. The inclusion of button prompts and suggestions like the above are a way of circumventing issues which may arise caused by unfamiliar wordings.

4.3 Chatbot Characteristics

4.3.1 Human Qualities

Oliver displays some human-like qualities in conversation, which were included in its response bank by the developer. For instance, Oliver will occasionally use emoticons (see line 4 in excerpt 7 above). It will also use non-formal language such as ‘awesome’ as an affirmative response, and ‘Whoa!’ when clients send a message which Oliver perceives as containing profanity. When Oliver recommends that the client ask for help (using a ‘help’ keyword), and the client follows through, Oliver will also respond with “That’s what I like to hear!” This informality contributes to Oliver’s intended purpose of translating the legal jargon behind the GDPR into layperson-friendly English.

4.3.2 Question and Prompt Detection

On occasion, Oliver has trouble understanding the intended message of its client. One way in which it ensures that the client produces the correct type of utterance is the following:

Extract 10:

- 1 Oliver: Is there anything else that I can help with?
- 2 Client: what are my rights?
- 3 Oliver: Type ‘yes’ if you have another question or ‘no’ if you’re done
- 4 Client: yes

The request in turn 3 is prompted as a reaction to Oliver not understanding the client’s message in turn 2. Instead of understanding the client’s question as an implicit affirmative, Oliver does not recognise the meaning of the utterance, and sets up another layer through which the client

must pass. By reading a ‘yes’ input, Oliver begins waiting for a question, and it therefore is able to parse the next utterance correctly where it could not before, provided that the question falls within its knowledge base. Excerpt 8, turns 5 and 6 are examples of the question input failing to generate an acceptable response.

4.3.3 Keyword Prompts

Oliver determines which response to produce by picking up on certain keywords in clients’ messages. For instance, given the question “What is GDPR?” Oliver has a pre-set response which it provides. Oliver also contains a further response to profanity, suggesting the user does not use “that kind of language”. This model of chatbot development can occasionally backfire, as simply latching onto keywords does not necessarily allow Oliver to understand the utterance meaning fully. For example, the following excerpt shows the client user attempting to ask about consent with regard to GDPR, but the question is phrased in the negative. Oliver successfully resolves the keyword ‘consent’, but fails to parse the negative phrasing.

Extract 11:

- 1 Client: What if i did not give consent
- 2 Oliver: Consent is another word for permission . Withdrawing your consent can either mean that: 1. You no longer grant permission for your personal data to be used at all, in which case your service will probably need to be terminated. 2. It can also mean that you withdraw your permission on some aspects of the service you are receiving, while leaving it in place for some others, in which case your service is likely to be only partially affected.

In some cases, a keyword alone is sufficient to receive the desired response, and some clients use this fact.

Extract 12:

- 1 Oliver: Great! Just type in the right that you want to know more about :)
- 2 Client: access
- 3 Oliver: GDPR gives you the right to get information from a company that may be processing your data and to be told: 1. What personal data they're holding on you, 2. The reasons for that processing, 3. Who can see it or who it gets sent to, 4. The period for which they plan to hold your data, 5. And from where they got that data.

A successful variant on the keyword model is the following excerpt:

Extract 13:

- 1 Client: Is gdpr the same in Ireland if i am maltese living in scotland?
- 2 Oliver: Although GDPR is the official law across the entire EU, it also applies to those companies that are based outside the EU if they use personal data of Europeans. This means it's a pretty far-reaching law, and many companies outside the EU have now fallen in line with it. It's also the reason why you've probably heard about the GDPR on the international news.

The above excerpt has the client ask about the countries in which the GDPR applies. While Oliver's answer is not quite what the user was asking about, it demonstrates how Oliver was successfully able to resolve the names of several countries and offer a related answer. The

ability to link one message to another is a crucial feature which allows Oliver to respond to questions and other prompts, and follows one turn with another.

4.4 Conversational Norms and Patterns

4.4.1 Turn-Taking

The turn-taking model proposed by Sacks et al. (1974) indicates that turns should generally be traded back and forth between interlocutors, with the exception of instances in which the current speaker elects to continue. The formulation of the conversational agent follows this pattern in a very precise manner, with the exception of the chatbot's turn formulation. Additionally, Oliver allows exactly one message to be sent by the client at a time, denying the client the ability to keep the floor. In spoken conversation, the definition of a turn is more of a semantic, syntactic, prosodic, or pragmatic structure (e.g. Sacks et al., 1974, p. 722-723). However, this definition must be reworked within the context of CMC. As each message is composed in its entirety before being sent to the other user, there is no opportunity for a new turn to be inserted in overlap. The only time at which another interlocutor can take the floor is once a message has been sent. Therefore, it would make sense to consider a single sent message to constitute a 'turn'.

As Oliver has all possible responses stored in a database, retrieving and outputting a message is instantaneous. Therefore, there is no room for either interlocutor to produce an overlapping turn. Oliver additionally produces several turns at once, and these are sent in quick succession. In response to the initial 'General information' button input, as shown in Figure 4, Oliver produces the following turns:

Extract 14:

- 1 Oliver: Okay! The General Data Protection Regulation (GDPR) is a law applicable from 25th May 2018 across the EU aimed at protecting personal data of individuals. Thanks to GDPR, it's much easier for EU citizens to understand how their data is being used, and also raise any complaints should this be necessary.
- 2 Oliver: If you are still curious about GDPR, hit the 'I do' button and I will give you some examples of what you can ask, else just click 'I don't' 😊

In between these two turns, the user is not given a chance to respond. Once Oliver sends the required messages, it waits for precisely one client message, after which it attempts to give another response. For instance, this extract in which the user attempts to reset the conversation demonstrates this pattern:

Extract 15:

- 1 Client: Restart
- 2 Oliver: To start over a conversation just type 'start over', wait for my ok, and ask away and GDPR question you might have. Go ahead ;)
- 3 Client: start over
- 4 Oliver: ok
- 5 Client: help
- 6 Oliver: Here... let me help you :) Do you need help in how to start over a conversation, or do you need to know what you can ask me?

In extract 15, turn 2 contains Oliver's instructions to the user, which explain the turn-taking procedure employed by the chatbot. The client is specifically told to wait for Oliver to give the

OK before attempting to send any other messages, possibly to avoid extra input while it is processing the restart request.

In the HHI dataset, turn-taking largely followed the Sacks et al. (1974) model, with each participant taking one turn at a time. An exception to this model occurs when the client-role participant asks two questions within the same turn, and the agent takes two separate turns to answer both questions individually.

Extract 16:

- 1 Client: Hello good day, i would like to know more about GDPR. Can you tell me what GDPR is and how it affects me? Thank you.
- 2 Agent: Good day! Thank you for contacting us for more information regarding our GDRP Regulations. GDPR stands for General Data Protection Regulation.
- 3 Agent: GDPR are a set of rules and regulations related to personal and prinvite information of users who reside in an EU Country. These regulations grant you the following rights:
 - The right to delete data about you
 - The right to withdraw consent
 - The right to get access to your data
 - The right to obtain a copy of your data
 - The right to rectify data
 - The right of data portability

In the majority of other instances, each topic is restricted to a single turn. The following extract occurs just after Extract 16.

Extract 17:

- 1 Client: Were there any privacy laws before then?
- 2 Agent: Yes. The previous laws were created in 1995 but did not account for smartphones or social media.
- 3 Client: And if i find myself in need of GDPR what should i do?
- 4 Agent: Forst thing you can do is file a complaint with your company. If you do not get a satisfactory response, you may contact the Data Protection Authority in your country.
- 5 Client: Ok thanks for your time have a good day

An interesting potential feature of computer-mediated communication is displayed in the extract above. Turn 5 contains three individual utterances which have been condensed into one single message. In the spoken modality, these utterances would likely have occurred in a closing sequence in which the client spoke one at a time, alternating with their interlocutor's responses. However, the quasi-synchronous nature of CMC allows the participant to produce all three utterances at once, breaking free from the usual turn-taking model and ending the conversation within a single turn. Schegloff (1992) discussed procedural consequentiality, in which the very technology mediating the conversation changes the procedures by which the conversation would be conducted. The ability to compose three separate utterances within a single turn changes the formation of turn sequences in CMC, as interlocutors have no opportunity to self-select until after the turn has been produced. It is a form of multitasking referred to as 'batching' by Falzon (2009, p. 11), in which utterances are grouped into a single turn and progress simultaneously across adjacent turns.

4.4.2 Adjacency Pairs

The orientation to complete adjacency pairs is a fundamental characteristic which is included in every chatbot, especially an information-seeking one like Oliver. After some of its turns, Oliver will prompt the user by asking if there is anything else they wish to know, as seen in this extract here:

Extract 18:

- 1 Oliver: You have the right to know the other source or sources of your data. This means that you can also check if you granted your permission to those sources to share your data with others.
- 2 Oliver: Can I help clarify some other GDPR questions?
- 3 Client: Yes please

Oliver will tend to add a turn to its messages. This extra turn often contains suggestions in the form of button inputs or text prompts (see section 4.2 for more information), or it may instead prompt the user for another question, as in turn 2 of Extract 18.

Extract 18 shows just one example of the questions that Oliver might ask the user. However, the user may choose to not orient to the first pair part (often complete with sample responses in the form of buttons). The following extract takes places immediately after Oliver's initial greeting, which means the user has been presented with the 'General information' and 'My Citizen Rights' buttons from Figure 4.

Extract 19:

- 1 Oliver: Hello! It's Oliver, here to help you discover how GDPR affects you as a citizen.
- 2 Oliver: Here are some useful tips: 1. If you know exactly what you want to ask, go ahead and type your question. 2. Should you get stuck and want to restart the

conversation type ‘start over’ or type ‘help’ to see what I can answer 😊 3.

There are two main areas I can help with; questions related to specific rights and also questions in general about GDPR.

3 Oliver: Choose one of the areas or ask a question 😊: - <General Information> <My Citizen Rights>

4 Client: hello

5 Oliver: Hey! Let’s get started on GDPR. What would you like to know? :)

Note: Phrases enclosed in angle brackets represent button input options that were offered to the client at that point in time.

In Extract 19, the client chooses to ignore the prompts in Oliver’s opening turn in favour of responding to its greeting. Oliver orients to the unorthodox utterance and responds in kind, but redirects focus to the topic of the original first pair part immediately afterwards, effectively seeking a response to the original question. It is worth noting that Oliver does not pursue specific responses to questions it asks, but generally seeks to keep the topic of conversation on GDPR.

An anomalous violation of Oliver failing to associate a client second pair part with its correct first pair part is shown below. It is an interesting example of Oliver possibly placing a higher priority on one first pair part over another, such that a client message which could be a response to either message is incorrectly matched to the wrong one.

Extract 20:

1 Oliver: Do you want me to show you a template on how you could request a company to delete your data?

- 2 Client: Do I need to delete research data?
- 3 Oliver: Type 'yes' if you have another question or 'no' if you're done :)
- 4 Client: yes
- 5 Oliver: Music to my ears! Just click on the link below to view the template. Remember this is just a suggestion, you can edit it as you please :)

Oliver's response in turn 5 implies that it took the client's 'yes' to be a response to the question in turn 1, rather than the message in turn 3. This may hint that Oliver was still expecting a response to the turn 1 question, and its own suggestion that the user type 'yes' did not override this.

In general, HHI conversations complete adjacency pairs more successfully. Questions asked by clients are often resolved with satisfactory answers. Extract 17 demonstrates a good example of this, as every question has a corresponding response. Like the example shown in Extract 19, greetings are often linked with initial question-containing turns, as in the extract below:

Extract 21:

- 1 Client: Hello good day, i would like to know more about GDPR. Can you tell me what GDPR is and how it affects me? Thank you.
- 2 Agent: Good day! Thank you for contacting us for more information regarding our GDRP Regulations. GDPR stands for General Data Protection Regulation.

In Extract 20, the greeting-greeting pair is split across turns 1 and 2, but each half shares its turn with a question and answer respectively. As a consequence of the technological context, which allows participants to combine utterances in a single turn without losing the floor (as described in section 4.4.1), as well as the persistence of chat messages, the agent is able to

respond to the greeting without failing to provide a response for the questions in the second half of the client's message.

4.4.3 Openings, Closings, and Politeness

Every HCI conversation is begun by Oliver introducing himself, then immediately getting into the topic of conversation. As discussed in section 4.4.1, and shown in Extract 19, Oliver's opening sequence is a three-turn sequence in which it gives a greeting, then immediately moves onto the topic of conversation (see Extract 19, turns 1-3), which may discourage users from providing their own greeting. Figure 4 shows the last message in Oliver's opening, which, as shown in section 4.4.2, is a first pair part of a question-answer sequence. Therefore, Oliver's greeting is rarely answered, with examples like that in Extract 19 being the rare exception.

As discussed previously (see section 4.4.2, excerpt 20), openings are still present in HHI conversations, albeit not in dedicated turns as they would be in the spoken modality. Interlocutors typically acknowledge a greeting when it is presented to them by a human agent, even if they are then given more content to respond to in the same initial turn. It can therefore be inferred that interlocutors feel less of a need to exhibit polite behaviours with a chatbot than they would with a fellow human.

HCI closings were relatively rare. To understand what Oliver identifies as a closing, I will demonstrate the pattern it takes when the client wishes to end the conversation. Throughout the conversation, Oliver continues to prompt the user for further questions. At any point, the user is free to type 'no', which Oliver takes to be an initiation of a closing sequence. Once Oliver receives the signal that the client wishes to shut down the conversation, it acknowledges the request and asks the user to rate its performance. The user may rate their experience, or

manually decline to do so, and Oliver then thanks the client for their time, which ends the conversation. For example:

Extract 22:

- 1 Oliver: Do you have more question for me?
- 2 Client: Not really
- 3 Oliver: No problem. Can you please rate our conversation before we part ways?
- 4 Client: <Neutral>
- 5 Oliver: Perfect, your input is greatly appreciated

As Oliver will produce the “how would you rate your experiences” turn every time it detects that the user intends to end the conversation, it is a good measure of the rate of participants who ended the conversation in a natural

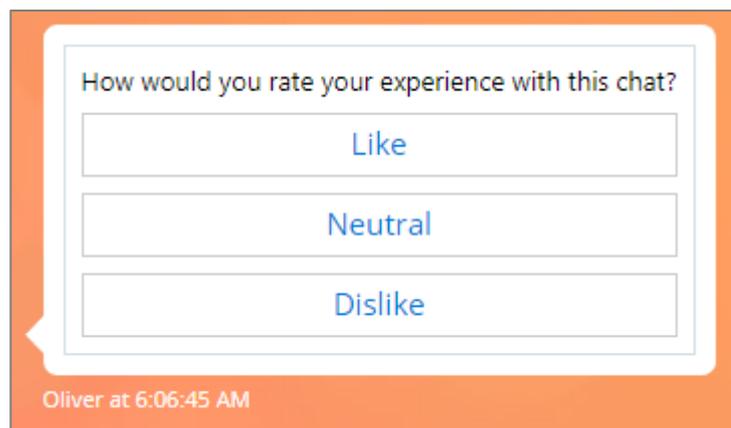


Figure 6: Oliver's rating options

way, rather than simply closing the browser window. Out of a total of 72 participants, only 20 of them reached a point at which they were asked to rate Oliver. All other participants abruptly terminated the conversation without a resolution.

The HHI conversations followed more conventional patterns. Conversational closings either consisted of one or two turns, with no pre-closing sequences. One-turn closings were exclusively produced by client users, who likely had more liberty in deciding when to end the conversation. On the other hand, two-turn closings always consisted of a first pair part from

the client, who initiates the closing, and a second pair part from the agent, who acknowledges the end of the conversation.

Extract 23:

- 1 Agent: Due to technological advancements since 1995, the data protection laws did not consider social media or smartphones. In order to fully protect their citizens, the GDPR regulations were drafted with any possible scenario as citizen can face in the current social and technological climate.
- 2 Client: Thanks for the information and clarifications
- 3 Agent: You're welcome. Should you require any more information, do not hesitate to contact us.

Extract 23 above is a typical example of a two-turn closing used in the HHI conversations. No pre-closing preceded this exchange. The agent is able to accept that the client wishes to end the conversation, and simply offers to continue their information-providing service if the client is in need of more details. Closings are overall more protracted in HCI conversations due to Oliver's request for a rating, which causes each closing to use a minimum of four turns.

The rate with which HCI conversations are abruptly terminated compared to the certainty with which HHI conversations were correctly closed indicates that people likely feel the need to be polite to a much lesser extent when speaking to an artificial intelligence, both when opening and closing conversations.

4.4.4 Repair

In HCI, instances of first-position self-repair are hidden from other interlocutors in the conversation, as turns are composed and reformulated before they are visible. Additionally, the

design of the chatbot eliminates second-position repair, as users cannot make two consecutive turns, and Oliver does not possess the ability to interpret the intentions of its clients and correct their utterances. However, instances of third-position self-repair are still visible, as in this extract:

Extract 22:

- 1 Client: elp
- 2 Oliver: Whoa! I strongly suggest that you don't use that kind of language. 😞 But I am here to tell you information related to GDPR, so let's get back to it! What would you like to know?
- 3 Client: help
- 4 Oliver: Here... let me help you :)

Here, the client mistypes the word ‘help’, which prompts Oliver to respond with the contents of turn 2. After this interjection, the client is able to correct their mistake by typing the word correctly, at which point Oliver responds in a more appropriate manner. Oliver does not directly call out the mistyped word itself, but its response makes it clear that the client’s utterance was unexpected, and therefore could not be parsed. Certainly, the client recognises Oliver’s utterance to be some kind of repair initiator, though it could also be interpreted as the introduction of a new topic.

Another way in which Oliver notifies clients that it failed to parse their message is by simply saying “Sorry, I didn’t understand that”. Once again, this kind of reply does not directly address the trouble source itself, as it is a generic response for any message that Oliver cannot understand. In the following example, the client is forced to reword their message:

Extract 23

- 1 Oliver: Hey! Let's get started on GDPR. What would you like to know? :)
- 2 Client: I would like to know about how it works
- 3 Oliver: I'm not sure what you are asking :(
- 4 Client: I want to know about GDPR
- 5 Oliver: There's lots of information available on GDPR, but the one thing you need to know is that your personal data belongs to you, and that you alone have the right to decide how that data is used, by whom and in what way. You're the king of your own data! 🏰

In Extract 23, Oliver cannot resolve the pronoun 'it' to GDPR, and therefore treats the utterance as an error. The chatbot initiates repair in its next turn, which causes the client to reword their message to include the name 'GDPR' itself. At that point, Oliver is able to parse the message and provide a response. It can be seen that, for HCI, repair is used as another tool which ensures that users use understandable language within the correct domain. Much like the button inputs provided by Oliver, and the occasional suggestion of questions that users may ask, repair as it is shown in Extract 23 is used to guide users towards the correct inputs.

In HHI conversations, repair takes something of a different form. The events which halt conversation in HCI, such as typos and misunderstandings, do not have so much of an impact on HHI conversations.

Extract 24

- 1 Agent: Forst thing you can do is file a complaint with your company. If you do not get a satisfactory response, you may contact the Data Protection Authority in your country.

2 Client: Ok thanks for your time have a good day

In turn 1 of Extract 24, the human agent misspells the word ‘first’ as ‘forst’. As the client does not orient to the potential trouble source, they clearly do not consider it severe enough that the conversation must be halted. However, looking at Extract 22, Oliver fails to understand its client when they misspell ‘help’ as ‘elp’. Human agents are more able to understand the meaning intended by their interlocutors, despite small errors that may occur. Larger errors may still necessitate brief halts in conversation, however, if the interlocutors determine that the meaning behind the utterance is lost due to the error.

Extract 25

1 Client: But how is GDPR different from the GDPR directive?

2 Client: * But how is GDPR different from the 95 directive?

In Extract 25, the client has noticed that they accidentally replaced ‘95’ with ‘GDPR’, which had been used earlier in the sentence. Of course, had the original utterance continued despite the error, the meaning would have been lost, and it would have likely prompted a repair initiator from the agent. In turn 2, the client orients to the trouble source, initiates the repair, and resolves the trouble source in a single turn. As is typical for chat conversations, the asterisk preceding the utterance indicate that it is to be a correction for an earlier utterance, which demonstrates that the client has oriented to the trouble source and intends to initiate repair. Next, the client repeats the utterance, but correctly replaces ‘GDPR’ with ‘95’, as was originally intended.

4.5 Informing the Design of a New Chatbot

4.5.1 Improvements

In the light of the above findings simple improvements that could be made to Oliver are:

- The addition of an autocorrect feature, so that it may resolve mistyped words without necessitating a repair sequence. The possibility for Oliver to attempt to resolve errors introduces the potential for other-initiated repair, as the chatbot can then produce turns which offer corrections.
- Expanding the knowledge base from which the chatbot draws its responses is also an important task, as there are instances in which participants attempt to ask valid questions. For example, in Extract 7, turn 3, the client asks which country proposed the introduction of the GDPR legislation, but Oliver cannot give an answer as there is no valid response in its knowledge base.
- Fine-tuning the keywords which guide Oliver's response selection and expanding the range of instances in which Oliver expects a keyword to be inputted. This would prevent issues such as that in Extract 20, in which Oliver cannot properly answer the question before the user types in a 'yes' to indicate that they wish to ask a question.
- To make Oliver more human-like, I would also allow clients a turn to offer their own greetings before initiating the topic at hand. This change might encourage more of a casual conversation, rather than clients perceiving Oliver as a search engine with limited conversational capabilities.
- Expanding the variety of responses which Oliver can output. Rather than simply matching keywords to pre-written responses, Oliver would benefit from a knowledge base of relevant documents, from which it could find the information required, and then automatically generate an appropriate response.

4.5.2 Evaluation

The first thing to implement was a simple autocorrect, which can cause the chatbot to detect misspelled words, and offer an alternative spelling.

```

Hello, my name is Toby. I'm here to teach you about GDPR!
Hello
Ask me anything you like!
daat
Did you mean 'data'?

```

Figure 7: Toby correcting a typo

In figure 6, the chatbot is given the misspelled word ‘daat’ instead of ‘data’, and is able to resolve the typo correctly. This improvement allows the agent to carry out other-initiations of repair in a more specific manner, rather than giving generic messages which do not necessarily reveal the error.

Next, implementing a check for profanity in the same method by which Oliver retrieves its responses: a list against which words are compared. In the HCI data, Oliver makes an error in identifying an utterance as profanity instead of a simple misspelling (see Extract 22). This sort of error is better caught by a spellchecker, rather than defaulting to the check for profanity.

```

what the hell are you saying
what
Sorry, I'm not sure what you mean. Please try again.
the
Sorry, I'm not sure what you mean. Please try again.
hell
Whoa! I suggest you don't use that language.
are
Sorry, I'm not sure what you mean. Please try again.
you
Sorry, I'm not sure what you mean. Please try again.
saying
Sorry, I'm not sure what you mean. Please try again.

```

Figure 8: Toby catches an instance of profanity

In the excerpt to the right, Toby responds to the word ‘hell’ with a successful triggered utterance suggesting that the user should not use inappropriate language.

Figure 8 also displays one of the shortcomings of the current implementation of Toby: it currently checks every word against the keywords and profanity lists, which results in the default response of “Sorry, I’m not sure what you mean” in the majority of cases. However, when encountering a keyword, Toby does return the correct output:

```
access
GDPR gives you the right to get information from a company that may be processing your
data and to be told: 1. What personal data they're holding on you, 2. The reasons for
that processing, 3. Who can see it or who it gets sent to, 4. The period for which the
y plan to hold your data, 5. And from where they got that data.
```

Figure 9: Toby responds to the 'access' prompt

One of the points addressed in section 4.4.3 is politeness. I noted that users rarely responded to Oliver’s first pair part greeting at the beginning of the conversation, as Oliver continues on to introduce the topic of conversation immediately. Toby gives users a chance to respond to the greeting before proceeding to the main topic, which can give the experience a more user-friendly and human-like touch.

```
Hello, my name is Toby. I'm here to teach you about GDPR!
Hello
Ask me anything you like!
```

Figure 10: Saying hello to Toby

The recommended improvements presented in this section to the design of Oliver should result in preferable conversation experiences, narrow the gap between HCI and HHI, and increase the efficiency with which clients are able to obtain information by interacting with Oliver.

In the final chapter, I first summarise the key findings of this study, and outline the improvements which can be made as a result of the findings discussed. I then present some limitations which I encountered, and list some potential directions for future research.

Chapter 5: Conclusion

The purpose of this study was to present a comparison between human-human (HHI) and human-computer interaction (HCI) from a pragmatic perspective, specifically looking at how chatbots handle conversational norms and the impact of the technological setting on the conversation. To these ends, the hypotheses presented in Chapter 1, section 1.2 were the following:

1. HCI openings and closings are structurally less elaborate than HHI counterparts. This can be realised in the form of omitted openings and closings or as shorter sequences. HHI openings and closings have a higher incidence of topically empty turns.
2. HCI conversations feature longer sequences from an interlocutor's introduction of their query to a satisfactory resolution.
3. HHI participants are able to resolve errors such as typos more easily and can often move past them without topicalising them.

The first hypothesis was proven true, as openings and closings were very frequently omitted entirely in HCI. Additionally, closings in HHI conversations contained more topically empty turns, in which interlocutors would simply say 'thank you' and 'you're welcome' to each other. The second hypothesis was also proven true, as HHI conversations were halted to a significantly lesser degree when errors such as typos were encountered. The third hypothesis was also successful. In every case in which a human participant in HHI made small errors, these were not oriented to and the conversation was not halted to allow participants to orient to and correct them. Repair occurred in cases of more significant errors, such as one which would have caused the utterance to be uninterpretable (see Excerpt 25).

The impact of the technology mediating the HCI conversations has on the nature of conversation in terms of the design of individual terms was also demonstrated clearly, in the significance of messages persisting on the screen and the affordance for interlocutors to produce multiple utterances in a single turn without losing the floor.

These findings are significant because the specific investigation carried out in this study is one which has rarely been considered in past research. One broadly similar study has been published (Hill, Ford, & Farreras, 2015), though it focuses primarily on more salient linguistic characteristics like emoticon usage. The usage of HHI chat data to inform improvements on current chatbot technology is a vital component of creating convincing conversational agents. By means of the chatbot Toby, I have sought to illustrate the sort and extent of improvements which could be implemented, with a view to more closely aligning chatbot interaction to HHI, consequently enhancing the user experience.

The primary limitations to this research were those of limited participant availability and technological constraints. In spite of my best efforts, participants were not readily available, which resulted in an imbalance of the respective numbers of HHI and HCI conversations. In future studies, gathering equal amounts of data should provide a measure of the significance or otherwise of this imbalance. The creation of a chat programme which includes button input in a similar way to Oliver's would also be helpful in drawing a clearer parallel between the two datasets, and might shed further light on the consequences of the technological medium on the organisation of the interaction. Additionally, gathering data by using screen recording software, rather than transcripts compiled after the fact, as was the method used by Meredith and Stokoe (2014), would shed more light on the occurrence of first-position self-repair in both HCI and HHI. Finally, a direct improvement to Oliver would be the implementation of natural language generation, which would allow the addition of a greater knowledge base to handle unforeseen questions without relying on pre-written responses.

The field of natural language processing still has a long way to go towards the creation of fully convincing, near-human chatbots which can truly replace human agents in all aspects, and the inclusion of conversation analytic methods as I have presented here can only serve to further our progress towards the ideal.

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Appendix A: Samples of HCI Data

Note: In the following samples, button input by the Client is denoted within angle brackets to differentiate it from typed input.

Sample 1

- 1 Client: can companies sell my data
- 2 Oliver: I didn't understand that sorry
- 3 Client: how is my data used by companies
- 4 Oliver: I'm not sure what you are asking :(
- 5 Oliver: Unfortunately I don't have the power to answer that at the moment. I suggest you type help to see what I can help you with 😊
- 6 Client: how is my data used by companies
- 7 Oliver: I don't understand sorry. Try asking "help" to see what I can do...
- 8 Oliver: I wish that I can help, but I don't know everything. Type help to see what I know 😊
- 9 Client: help
- 10 Oliver: Here...let me help you 😊
- 11 Oliver: Do you need help in how to start over a conversation, or do you need to know what you can ask me?
- 12 Client: <What to ask>
- 13 Oliver: Sure thing! As you know, I am here to help you understand better what GDPR is all about and how you can benefit from it as a citizen.
- 14 Oliver: There are two main areas I can help with; questions related to specific rights and also questions in general about GDPR. Choose your preferred area so I can give you some examples:

15 Client: <Rights>

Sample 2

1 Client: Can i send mail to people that didn't ask for

2 Oliver: Sorry, I didn't understand that

3 Client: Can i send emails to people whose didn't ask for it

4 Oliver: I'm not sure what you are asking :(

5 Client: what is gdpr

6 Oliver: The name makes it sound more difficult than it really is. In simple terms, GDPR is the new official law issued by the European Union that applies all across the EU.

7 Oliver: Basically it protects your personal data rights as an individual and restricts companies in the way they use your data. It is the leading law in the world on privacy and data protection.

8 Oliver: Is there anything else you would like to ask

9 Client: <Sure do>

10 Oliver: Glad to help! Go ahead and ask a question, but if you are unsure of what to ask, here are some examples:

11 Oliver: How does GDPR affect me? What is new in GDPR? What are my rights according to GDPR

12 Client: I'm a web agency what do i have to do to be conform with gdpr

13 Oliver: I don't understand sorry. Try asking "help" to see what I can do...

14 Client: help

15 Oliver: Here...let me help you 😊

- 16 Oliver: Do you need help in how to start over a conversation, or do you need to know what you can ask me?
- 17 Client: <What to ask>
- 18 Oliver: Sure thing! As you know, I am here to help you understand better what GDPR is all about and how you can benefit from it as a citizen.
- 19 Oliver: There are two main areas I can help with; questions related to specific rights and also questions in general about GDPR. Choose your preferred area so I can give you some examples:

Sample 3

- 1 Client: <General information>
- 2 Oliver: Okay! The General Data Protection Regulation (GDPR) is a law applicable from 25th May 2018 across the EU aimed at protecting personal data of individuals. Thanks to GDPR, it's much easier for EU citizens to understand how their data is being used, and also raise any complaints should this be necessary
- 3 Oliver: If you are still curious about GDPR, hit the 'I do' button and I will give you some examples of what you can ask, else just click 'I don't' 😊
- 4 Client: <I do>
- 5 Oliver: I like where this is going...You can ask me anything GDPR related, here are some examples:
- 6 Oliver: Can I know the source of my data? Do I have the right to be notified about things? What is the right to be forgotten? What are my rights?
- 7 Client: Can I know the source of my data?

- 8 Oliver: You have the right to know the other source or sources of your data. This means that you can also check if you granted your permission to those sources to share your data with others.
- 9 Oliver: Can I help clarify some other GDPR questions?

Appendix B: Participant Instructions for HHI Data Collection

Participant A

In front of you is a laptop. The chat window you see is connected to another human participant, who sees the same thing. You are also provided with the following information about the GDPR law, which you may or may not use. Should you choose to use the information, you may reword it.

You will be taking the role of ‘agent’ in a text conversation with the person on the other end, who will be acting as your client. He/She will seek information from you. You may respond in any way you see fit. Otherwise, you may conduct the conversation however you like.

GDPR Information:

<p>The GDPR grants the following rights:</p> <ol style="list-style-type: none"> 1. The right to delete data about you 2. The right to withdraw consent 3. The right to get access to your data 4. The right to obtain a copy of your data 5. The right to rectify data 6. The right of data portability 	<p>The GDPR law was enacted on May 25th, 2018.</p>
<p>The GDPR protects your personal data rights as an individual and restricts the control that companies have over your data.</p>	<p>Data erasure is the deletion or destruction of personal data held by a company. The specific procedure depends on the</p>

	circumstances and the services you were receiving from the company.
Before the modern GDPR was enacted, the previous laws were created in 1995, and did not account for smartphones or social media. The 2018 GDPR law accounts for modern circumstances.	GDPR stands for the General Data Protection Regulation.
You can file a complaint with the company at first. If you do not get a satisfactory response, you may contact the Data Protection Authority in your country.	

Participant B

In front of you is a laptop. The chat window you see is connected to another human participant, who sees the same thing. You are also provided with some questions about GDPR law. You may or may not use all of them, but please use at least three. You do not have to use the same wording presented here.

You will be taking the role of ‘client’ in a text conversation with the person on the other end, who will be acting as a customer service agent. He/She will respond to your questions. You may conduct the conversation in any way you like.

Questions:

- When was the GDPR enacted?

- What came before GDPR?
- What are my rights under GDPR?
- What does GDPR do?
- How do I complain about a possible data breach?
- What does GDPR stand for?
- Can I ask for my data to be deleted?
- Could I have some general information about GDPR?

Appendix C: Samples of HHI Data

Sample 1

- 1 Client: Hello good day, i would like to know more about GDPR. Can you tell me what GDPR is and how it affects me? Thank you.
- 2 Agent: Good day! Thank you for contacting us for more information regarding our GDRP Regulations. GDPR stands for General Data Protection Regulation.
- 3 Agent: GDPR are a set of rules and regulations related to personal and prinvite information of users who reside in an EU Country. These regulations grant you the following rights:
 - The right to delete data about you
 - The right to withdraw consent
 - The right to get access to your data
 - The right to obtain a copy of your data
 - The right to rectify data
 - The right of data portability
- 4 Client: How long have these been in effect?
- 5 Agent: The GDPR law was enacted on May 25th, 2018.
- 6 Client: Were there any privacy laws before then?
- 7 Agent: Yes. The previous laws were created in 1995 but did not account for smartphones or social media.
- 8 Client: And if i find myself in need of GDPR what should i do?
- 9 Agent: Forst thing you can do is file a complaint with your company. If you do not get a satisfactory response, you may contact the Data Protection Authority in your country.

10 Client: Ok thanks for your time have a good day

Sample 2

1 Client: hi good day, i have recently learned of gdpr. what does gdpr mean?

2 Agent: Hi there! GDPR is a policy that came into effect on May 25th, 2018, it protects your personal data as an individual and restricts the control that companies have over your information.

3 Client: what does gdpr stand for please?

4 Agent: GDPR stands for General Data Protection Regulation

5 Client: does that have anything to do with the data protection authority please?

6 Agent: Yes, the data protection authority is there to ensure that all the companies in your local country are following GDPR, if at any point you feel that your data has been breached by a certain company, we suggest you first file a complaint with the company and If you do not get a satisfactory response, you may contact the Data Protection Authority in your country and they will be able to guide you further through the process.

7 Client: is all my data protected or is it just specific data?

8 Agent: Any and all your personal data that is collected by a company is protected, if at any time you would like to remove or have your data erased from a specific company, each company has a specific procedure which depends on the circumstances and the services you were receiving from the company.

9 Client: thank you very much

Appendix D: Improved chatbot code

```

from spellchecker import SpellChecker

def check(sentence):
    spell = SpellChecker() #loads word/frequency list
    misspelled = spell.unknown(sentence.split()) #list of words which are not in
the word list
    for word in misspelled:
        answer = spell.correction(word) #correct any words which were not found in
the list
    return answer

if __name__ == '__main__':

    keywords = ['access', 'consent'] #All keywords lists can be expanded if
necessary
    profanity = ['fuck', 'shit', 'hell']

    print("Hello, my name is Toby. I'm here to teach you about GDPR!")
    #Allows greeting input before getting to the topic
    greeting = input()
    for word in greeting.split(): #allows user to say something like 'Hey Toby!'
instead of just Hey
        if word in ['Hey', 'Hello', 'Good morning']:
            print("Ask me anything you like!")

    question = True
    while question is True: #allow continuous input while the user has not exited
the conversation
        q = input()

        if check(q) is not None: #check for misspelling: if the answer string
returned is empty, no typos were found
            print("Did you mean '" + check(q) + "'? Feel free to input your message
again.")
        else:
            for word in q.split():
                if word in keywords:
                    if word == 'access':
                        print("GDPR gives you the right to get information from a
company that may be processing your data and to be told: 1. What personal data
they're holding on you, 2. The reasons for that processing, 3. Who can see it or
who it gets sent to, 4. The period for which they plan to hold your data, 5. And
from where they got that data.")
                    if word is 'consent':
                        print("Consent is another word for permission. Withdrawing
your consent can either mean that: 1. You no longer grant permission for your
personal data to be used at all, in which case your service will probably need to
be terminated. 2. It can also mean that you withdraw your permission on some
aspects of the service you are receiving, while leaving it in place for some
others, in which case your service is likely to be only partially affected.")
                    elif word in profanity:
                        print("Whoa! I suggest you don't use that language.")
                    else:
                        print("Sorry, I'm not sure what you mean. Please try again.")

            if q is 'help':
                print("I can help you figure out what you can ask me. How about
asking about the rights granted to you under GDPR?")

            if q in ['No', 'No thanks']:
                question = False
                print("That's okay, thank you for talking with me!")

```