Chapter 1

Introduction

Every day, we communicate through computers on projects ranging from a group lunch order to office presentations to critical medical decisions. And every day, we also *mis*communicate through computers: We don't pick up on an intentionally humorous response, or we miss the criticality of a request. This is made more frustrating because if these responses or requests were made in a face-to-face setting, these underlying intentions would be easier to pick up through tone of voice or the rate of speech, i.e. spoken prosody. My thesis aims to use timing patterns in typing, called *keystroke dynamics*, to detect these underlying motivations, and make the information normally available only in face-to-face interactions also accessible in a text-based interaction, where prosodic information is assumed to be lost.

This thesis explores text-based computer-mediated collaboration through multiple levels of granularity. These levels of granularity are important because conversations and user intent are best understood at multiple levels of context. For example, an utterance might be best understood through the context of the preceding utterance or an utterance might be best understood through the context of the entire preceding conversation. As a realization of this uncertainty, Faggioli et al. (2021) built a hierarchical conversational model that maps all dependencies from local semantic dependence within an utterance to dependencies between an utterance and the entire preceding conversation; this mapping allowed the researchers to better trace a single conversational thread through the entire conversation.

The notion of dynamic context in a conversation is fundamental to the task of conversational analysis, and thus is essential for understanding latent variables that are underlying an entire conversation (Park et al., 2018). Clark (1996) calls this "layering," in which common ground, which emerges throughout the course of a conversation, requires understanding an utterance at multiple levels of meaning. These multiple levels are created in a "context space," which ties together an utterance with the context necessary to understand it (Reichman, 1978).

It is also important for my thesis to investigate a conversation at multiple levels of granularity because causation and psychological intention often do not exist at the same level of granularity. For example, Peng et al. (2022) shows that while the cause of emotional distress can exist at the level of an entire conversation, the expression of distress or psychological intent may only exist at the level of a single utterance. Therefore, being able to study a conversation at multiple levels of granularity is essential for understanding the mindset that underlies the words of a conversation.

In addition to studying a conversation at multiple levels, this thesis also investigates keystrokes as an both independent variable for predicting mindsets, as well as a dependent variable that is predicted by a known mindset. The reasoning behind this is that these studies are designed to study correlations rather than causation. Because an instrument such as an experimental intervention was not used (cf. Liebman and Gergle (2016b)), it is difficult to make assertions about whether typing behavior causes changes in mindset or vice versa.

The work in this thesis uses keystroke patterns because the typing modality of language production combines the spontaneous and dynamic elements of spoken language production with the static elements of finalized written text (Barrett et al., 2018a; Chen et al., 2021; Pinet et al., 2016). Keystroke patterns include everything from typing speed (Bajaj and Kaur, 2013), to the location and duration of pauses (Medimorec and Risko, 2017), to the mistakes and revisions a typist makes (Brizan et al., 2015; Pinet and Nozari, 2021). These production patterns can illuminate cognitive processes and social dynamics that are not overtly evident from surface-level or visible word choice; however, these processes exist in the latent patterns involved in moment-by-moment production, and can provide insight into why a user is taking a certain action. While the ultimate aim of my thesis research is to make these patterns more immediately beneficial to human-to-human interactions through a computer, they should also be expanded and refined for human-to-computer interactions, e.g. talking to a chatbot. Making keystroke patterns evident to a human interlocutor might include converting typing patterns into a visualization that a message recipient can see; in the case of chatbots, this could mean sending a computer agent both word-based features based on visible message text, and also augmenting these with keystroke-based dynamic production features.

However, keystroke data, especially when collected remotely (as I do in my thesis) can be especially noisy and unpredictable. As a simple example, if a user pauses in their typing, there could be myriad reasons for the pause (Conijn et al., 2019): a typist could be thinking and planning or they could be distracted by a fly in the room.

Further, typing patterns are only revealing about a user when they can be compared to a baseline for that user. For example, if User A types faster than User B, this does not provide any information about the cognitive state of each user. Moreover it wouldn't even answer who the more adept typist is: User B could be a fast typer but is having a bad day. Although the studies in my thesis control for individual participants, the studies do not establish a baseline against which to compare typing patterns in the experimental dialogue.

Before proceeding though, it is important to acknowledge the ethical issues surrounding keystroke collection. This will be expanded upon in the Overall Discussion (Chapter 8) but it is critical to address at the beginning. Keystrokes are a biometric and can be used for identification, similar to a fingerprint or face recognition (Monrose and Rubin, 1997a). In addition to personal identification, keystroke patterns can also be used to identify demographics such as gender or education level (Brizan et al., 2015, inter alia). However most major internet browsers make it easy for developers to collect keystrokes (Acien et al., 2021). Thus, it is important to consider ethical implications when collecting keystroke information, as this information is both private and highly informative. Efforts are being made, though, to anonymize keystroke information so as to keep this information private (Monaco and Tappert, 2017).

To further complicate the establishment of a baseline typing pattern, it is also well-known that typing patterns differ depending on the task at hand, as well as the application within which they are typed (Barghouthi, 2009). While the experiments in my thesis were run in a single interface with a single experimental prompt, findings such as those in Barghouthi (2009) and subsequent studies point to the notion that keystroke patterns detected in one setting might not translate to another setting and therefore may be less generalizable. Despite these limitations of studying keystrokes, my thesis represents an important starting point for combining human-computer interaction with keystroke dynamics, while basing its hypotheses on principles from cognitive science.

While the application of my findings will be to benefit computer-mediated communication, my studies are also motivated by theories from the cognitive sciences. In particular, the Implicit Prosody Hypothesis (e.g. Fodor, 2002b, and expanded on in Section 2.1) can provide insights into why cognitive processes loom large over typing production. Implicit prosody posits that even when people are not speaking out loud they still use prosody when reading silently or typing. The evidence for this is that "hearing" a voice in one's head helps to add structure to language, and is seen in eye tracking or comprehension tests (Breen, 2014a). As such, one aim of my thesis is to elucidate how typing patterns parallel spoken prosody so that the information contained in spoken prosody, e.g. altered meaning from a different tone of voice, can also be used in a text-based environment.

As an example, when we speak to a person we dislike, we tend to use a different tone-of-voice, a different speaking rate, and make different word choices (Fujie et al., 2004). In response to a terrible idea, we may say *That's a great idea!* but the phrase is laden with irony and its facetiousness is readily evident. In text-based communication, while we can sometimes use fonts (Heath, 2021), emoticons (Yuasa et al., 2006), or punctuation (Gregory et al., 2004) to convey prosody, often the correlation between (written) orthography and (spoken) prosody is insufficient or misunderstood (Heath, 2021). As a result, our understanding of our relationship with an interlocutor may be inaccurate and uncertain.

My studies aim to understand the underlying mindset or sentiment of a user, in order to make text-based communication more multi-dimensional and better represent the true intentions of speakers.[1] However, see the Overall Discussion, specifically Ethical Considerations, for a discussion of circumstances in which a user may not *want* their true intentions or mindset to be known to their interlocutor.

1.1 Studies Overview

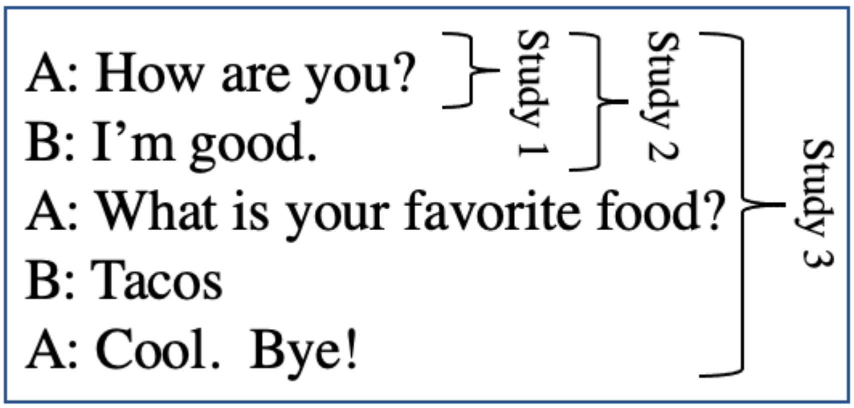

Figure 1.1
A comparison of the scope of each of my studies. Study 1 looks at the dialogue act functions of an individual utterance; Study 2 looks pairs or *dyads* of utterances; Study 3 looks at entire conversations.

For each conversation, I used crowdsourcing to randomly pair two participants, who engaged in a 16-minute conversation. One participant began by discussing their movie and television preferences, and then the other participant provided recommendations. I collected timing information on every keystroke, as well as the final transmitted message.[2] I then used various machine learning techniques, ranging from linear models to neural networks, to study the connections between keystroke timing and features of conversations.

The three studies were structured as follows:

[1]As a note on terminology, I will often use the term *speaker* to refer to the person producing language, whether they are speaking out loud or producing messages in a text-based environment.

[2]Details of data collection are provided in Chapter 4.

Study 1 - Utterance-level dialogue acts: An utterance's functional purpose in a dialogue will change the way the words are typed. When engaged in a conversation, some utterances are intended to make reference to previous remarks, e.g. a clarifying question, while other utterances are intended to progress the conversation forward, such as a statement introducing a new topic. The function of an utterance is referred to as a dialogue act (Stolcke et al., 2000). Sometimes the same or similar words can function in both of these capacities. For example, in the dialogue *A: It's nice outside. B: Okay*, B's response could convey different messages: *Okay* can be said as a statement, to acknowledge A's assertion, or *Okay* could be said inquisitively, as if to question why A made that assertion. This can be confusing in a text-based communication context, since an interlocutor only receives the static or final word-form, rather than any inflection or timing patterns, where these features can be informative as to whether the utterance is, e.g., referring to previous utterances or is being used to introduce a new topic (Lai, 2012).

Study 1 aims to differentiate between typing patterns of dialogue acts that require very different responses. In the example above, A's response to *Okay* should look very different depending on whether B's utterance was an acknowledgment or a question. In addition, Study 1 investigates whether 8 primary types of dialogue acts have unique typing patterns associated with them. These findings are useful for elucidating the cognitive properties that underlie the production of different dialogue acts, and whether certain dialogue acts require more or less cognitive effort to produce.

Additionally, findings such as those above would parallel findings in studies such as Dhillon (2008), which found similar pause differences in spoken language production. By illustrating these parallels, it demonstrates the correspondence between spoken prosodic difference and type-written timing differences, allowing future researchers to design text-based algorithms, such as chatbots, using principles derived from spoken prosody.

Study 2 - Turn-level sentiment analysis: Study 2 analyzes sentiment at the conversational level. The first half of the study uses a collection of keystroke predictors to predict sentiment categories, such as positive, negative, extreme and neutral. Since these sentiment categories have been shown to be detectable in isolation, e.g. Brizan et al. (2015), this part of Study 2 also acts to demonstrate the sentiment findings from typing in isolation also extend to typing in dialogue.

However, dialogue is unique in that it is a joint action, and should not be considered in isolation (Clark, 1996). As such, Study 2 also investigates elements of sentiment that are unique to dialogues. Rather than studying only the sentiment of an isolated utterance, Study 2 also looks at how *change* in sentiment between utterances affects typing production patterns. In addition, a user will naturally form an opinion of their conversational partner, whether in spoken conversation or text-based conversation (Koudenburg et al., 2017; Murray et al., 2010). As such, Study 2 used regression modeling to determine how typing patterns are affected not only by the sentiment of an individual utterance but also by the user's overall opinion of their conversational partner.

Study 3 - Conversation-level rapport: Study 3 investigates whether the level of rapport experienced by conversational partners can be predicted using typing patterns. This is important for communication because in many settings – conversing with a friend, a customer, or a medical patient – establishing rapport is important in order to achieve successful collaborative outcomes, such as better peer tutoring (Olsen and Finkelstein, 2017) or patient satisfaction in a therapeutic setting (Leach, 2005).

This study uses participants' self-reported impressions after the experimental conversation, which asked them to measure aspects such as rapport, enjoyment, and self-awareness. It then builds machine learning models using keystroke-based features to accurately predict a typist's sense of established rapport.

Study 3 also looks at how different subsets of the conversation can predict rapport, where subsetting either looks at timing slices of a conversation or focuses only on certain roles that a participant is playing. This is important because rapport prediction is helpful *during* a conversation, where making adjustments to perceived rapport can improve the outcome of an interaction (Gidron et al., 2020). Moreover, in a setting such as a customer service interaction, the person of interest would be the customer, who is only receiving, not providing, service.

Each study investigates dialogue at different levels of granularity: single utterances, pairs of utterances, and entire conversations. Since my goal is to ultimately make the underlying motivations of latent typing patterns salient to a partner, it is important to only extract the most relevant data that is actually connected to those motivations, rather than extracting every pattern in typing production.

My thesis is structured as follows: In the next two sections of the introduction, I review the motivations for my thesis research and then enumerate the research questions that each study will answer. Chapter 2 then reviews prior literature that is relevant to the entire thesis. Chapter 4 explains how the data was collected for my thesis and exactly what data was collected. Chapters 5, 6 and 7 each contain the individual studies of my thesis. Each of these chapters reviews specific prior literature, explains results, and then includes a discussion of that specific study. Finally, Chapter 8 ties together each of the individual studies in this thesis and provides an overall discussion of how each study elucidates the central theme of my thesis.

1.2 Motivation

1.2.1 Importance of better understanding text-based CMC

The COVID-19 pandemic, and its effects on remote working, have added a tragic emphasis to the need for a better understanding of computer-mediated communication, as text-based CMC has come to occupy an even more central role in our lives. In a Pew Future of Work study from December 2020, researchers reported that 57% of respondents often or sometimes use chat-based platforms such as Slack or Google Chat (Pew Research Center, 2020).

Interestingly, when compared to video-based platforms such as Zoom, text-based platform usage was consistent across educational and income demographics. On the other hand, for video-based communication platforms there was a clear divide with better-educated and higher-income individuals using these platforms more often.

This shifting platform usage trend has a strong effect on the work environment, especially as "Generation Z" enters the workforce with very different technology expectations than prior generations, specifically in expecting more remote work and remote communication tools (Janssen and Carradini, 2021). The 2021 Work Index Trends report from Microsoft notes that a manager's role is increasingly centered around keeping a team connected and monitoring employees' well-being and mindset (Microsoft, 2021). However, Muir et al. (2017, p. 526) points out that when power relationships are asymmetric, e.g. a (higher-powered) manager and a (lower-powered) employee, "managers can find maintaining positive working relationships and good levels of rapport with virtual team members particularly challenging when relying on instant messaging to communicate." While it is impossible to remotely interact with every employee multiple times a day, as a manager might do in a physical office, keystrokes provide a unique way to do just that.

Importantly, though, in comparison to straightforward email monitoring using keywords, keystroke patterns also offer anonymity, in that keystroke patterns can be analyzed independently of the actual lexical content of what is being typed (see Section 2.2.6). This can be thought about with an analogy to spoken language: If a close friend is especially stressed, but their words are hard to discern, we can usually still tell that it's our friend and that they're stressed because of the uniqueness of their voice and spoken stress patterns. Similarly, keystroke patterns can offer this same level of unique anonymity, where timing patterns are unique, regardless of the actual words being typed. At the same time, insights at this level of cognition raise serious ethical and privacy issues. These are addressed regularly in my thesis, as well as in the IRB submitted and approved for data collection (Section 4.4.1).

As of this writing (March 2023), while many workers are returning to their physical offices, 36% of workers are still working remotely (Flynn, 2022). While Zoom usage will likely be replaced by face-to-face meetings in physical offices, text-based communication will also likely still retain a more central role given its wider usage in work settings. (It will be very helpful to revisit this in the future, but given the popularity of platforms such as Slack and Microsoft Teams before the pandemic, it seems unlikely that their usage will suddenly shrink.) Regardless of how these trends continue to change in the immediate future, text-based CMC plays an important role in our day-to-day routines. This points to the importance of my thesis, as I aim to better understand the latent emotions and thoughts that lie behind the salient text that interlocutors see in text-based communication.

1.2.2 Ubiquity of Computer-Mediated Communication

To understand society's changing work and lifestyle settings even more profoundly, it is best to reflect on the title of Gergle (2017), "Discourse processing in *technology*-mediated environments" (emphasis added). Although "computer"- and "technology"-mediated environments are synonymous in many respects, subtle and less-subtle differences exist. The most apparent difference is that computer-mediated environments seem to conjure pictures of a user sitting down and using a laptop or desktop computer to communicate via a chat-based client such as Instant Messaging. Technology-mediated environments, though, seem to expand this picture to scenes such as controlling a smart TV with your voice, or engaging in a video chat on a smartphone.[3]

The difficulty, though, arises from the sources of information missing in these (non face-to-face) contexts. For example when chatting online with a customer service agent we do not have physical knowledge about the agent, such as facial expressions, and we cannot even be sure of their name or age. We use all of these to help make more informed decisions about how to communicate more efficiently. We also use information from prosody, such as rising or falling tones, as well as hesitations or rewordings (e.g. Fodor, 2002b; Shriberg et al., 2000; Snow, 1994; Trott et al., 2019). Given this, many early CMC researchers, using traditional communication principles, concluded that CMC is an impoverished environment, with narrow bandwidth and limited social presence (Walther and Parks, 2002). However, research such as Reid et al. (1997) then posited that social presence simply takes a longer time to develop via CMC, and so using the same timeframe to

[3]Although new technologies such as smart TVs may use mobile-based, touchscreen communication, the studies in my thesis were all completed on desktop or laptop computers, with full QWERTY keyboards. Nonetheless, one motivation for these studies is that they are first steps in understanding more broad phenomena such as mobile communication. Once fixed-keyboard communication is more thoroughly understood, it can be extended to (often noisier) mobile-based communication.

compare CMC to face-to-face communication does not provide an accurate picture of CMC. In my own work, this is one of the reasons for a longer experiment with a starting prompt, so that participants have more time to develop a relationship.

One of the main goals of this thesis, then, is to show that the information traditionally considered to be limited to face-to-face interactions or even audio/visual online conversations, is actually available in latent information available in keystroke patterns. This, then could add support to the Social Information Processing (SIP) theory (Walther, 1992). If reported rapport between participants is still high, and participants still exhibit and take advantage of differences in timing patterns, it could provide evidence for a central tenet of SIP: "...communicators are just as motivated to reduce interpersonal uncertainty, form impressions, and develop affinity in on-line settings as they are in other settings." (Walther and Parks, 2002, 535).

However, given that much of this information might only be present in latent keystroke timing patterns, designers could use the results of my thesis research to make this latent cognitive information more overt. This is underscored by Tidwell and Walther (2002)'s argument that unlike face-to-face communication, CMC offers individuals only limited opportunities to observe others unobtrusively or to gain information about them indirectly. But by using keystroke patterns to make information about mindsets more overt, we can enrich the CMC environment to allow for more successful interactions and collaborations.

1.2.3 Uniqueness of keystroke dynamics

While my thesis is focus on typing and keystroke patterns, research into spoken language research is exploding, with good reason (Sisman et al., 2021) More and more companies are turning to voice assistants for customer service, troubleshooting, and even solving complex issues (Rozumowski et al., 2020). In combination with these developments, more and more products are adding the capability to control devices with voice commands, from cars to televisions to toaster ovens. As such, there are many good reasons to be pushing ahead with research into spoken-language conversational research.

Procedure	Keystroke Research	Speech Research	Text Analytics
Data collection	Trivial using a keylogger and non-obtrusive	Can be non-obtrusive using just a microphone, but Svec and Granqvist (2010) shows, because different microphones often have different sampling rates and sensitivity levels, inter-microphone comparison is often difficult if not impossible.	Trivial using e.g. a Google Form or web-scraper
Measuring production data	Trivial, including disentangling overlapping keystrokes from different users	Extracting timing data from speech can be extremely complex and labor-intensive. The average time for measuring word onset is 4 hours for 1 hour of speech (Bazillon et al., 2008; Novotney and Callison-Burch, 2010). The task multiplies in complexity when voices are overlapping.	Timing data is not available for most written data. For research such as Kalman et al. (2013a), the timestamps when a message was sent are sufficient.
Available features	Timing, edits, final version	Timing, edits, final version	Final version

Table 1.1
A comparison of research stages in keystroke analysis, speech analysis, and text analytics. Most of these steps are more straightforward and simple in keystroke research.

That being said, we still use, and specifically type on, computers *a lot*. Statistics show that we spend upwards of 10 hours a day using technology, and it is not uncommon for technology use to be described as “nearly constant” (Twenge and Farley, 2021). Especially with a move towards more remote work arrangements, what was formerly “water cooler” chat can be replaced by an SMS text message or a direct message on Slack. To play on an old workplace cliche, many meetings *are* becoming emails.

Focusing specifically on improving CMC, keystroke research presents many advantages over research using other modalities of language production. To gain a better sense of this, Table 1.1 compares typing research to other modalities of language production, which should illuminate the relative advantages of this type of research. In the tables below, “text analytics” consists of fully written text in a final static form. For example, this could be an essay on a test or an email sent to a recipient. This excludes research into the process of writing, where content is being dynamically produced, possibly by hand, e.g. pen and paper. “Speech research” consists of studying vocal language production, whether a monologue or an interaction involving two or more participants.

1.2.4 Parallels to the Implicit Prosody Hypothesis

Studies such as Goodkind and Rosenberg (2015), Plank (2016), and Barrett et al. (2018b) show that timing phenomena present in speech data are also present in typing data. Fodor (2002a) describes this as "silent prosody" or the Implicit Prosody Hypothesis (see Section 2.1 for a full explanation of the theory and terminology). This is the phenomena experienced when a person is producing or comprehending language silently while still being affected by non-explicit prosodic contours. For example, when reading silently, people often still hear a voice in their mind, where this voice is akin to an out-loud voice with pauses and tone. This voice adds prosodic contours to static text, and is reflected in the speed at which people read different parts of the text.

The same phenomenon applies to typing, where even though people are *producing* language rather than comprehending it, they still hear a voice in their mind as they type, whether the person is interacting with another agent or producing a thesis in solitude; importantly, this silent "voice" alters the speed at which people type. Although my thesis does not explicitly investigate the precise parallels between spoken prosody and silent prosody in typing, many of the typing features I use have an analog in spoken language.

This is important because (explicit) prosody, i.e. prosody that is audible in a spoken language or visible in a signed language, signals everything from importance of the words being produced (Swerts and Geluykens, 1994), to how much the words being produced are part of shared knowledge or common ground (Mushin et al., 2003), to when a speaker is planning to yield the floor to their interlocutor(s) (Gravano and Hirschberg, 2009). By looking at similar phenomena in Implicit Prosody, it becomes possible to understand which timing-related choices exist only in the mind, compared to those timing adjustments that are explicitly produced and only intended to aid spoken interactions. These timing features in typing can then be used to infer underlying cognition or motivations behind the words being typed.

Just as prior research on typing, such as Priva Cohen (2010), Logan and Crump (2011), and Plank (2016), has shown that findings in typing research can apply to the larger domain of cognitive science, the studies in my thesis can have the same type of benefit.

1.2.5 New keystroke dataset

The data collected for my thesis is also now publicly available. The corpus, called the Keystrokes in Dialogue (KiD) Corpus, is located at https://github.com/angoodkind/KiDcorpus. As of this writing (March 2023), the public repository is not complete; however, the following data will be made available:

- The full keystroke logs for each participant, complete with timing data
- The full message text and timing for each participant
- The survey responses from each participant, covering their impressions of their partner and the conversation
- Basic demographic information for each participant, including age, gender, and education level

1.2.6 Theoretical contributions

My thesis also makes contributions to three areas of inquiry: Human-Computer Interaction, Language Prosody, and Keystroke Research.

1.2.6.1 Human-Computer Interaction

My thesis focuses on human-to-human computer-mediated interaction, and studies the information that is present in the latent patterns of keystrokes. In the future, this information can be used to make social information more visible to conversation partners, for example by displaying a visualization of typing patterns that represents their mindset, so that one speaker can understand that their partner is excited or confused.

Adding explicit typing data to text-based CMC would add valuable empirical data to the social influence approach to media richness, as well as the channel expansion theory (Fulk et al., 1995; Walther, 2011). If adding typing data to CMC changes a user's perception of that modality and they elect to use it for more purposes, this bolsters support for a theory such as channel expansion, which posits that properties ascribed to various mediums are not fixed (Carlson and Zmud, 1999; Walther, 2011). This would also point to the limitations of media richness theory, which defines media richness based on *a priori* properties of media.

On a more practical level, this would also invite designers to use text-based CMC for a wider array of purposes. Channel expansion theory's core argument is that as individuals gain more experience with a particular communication medium, the medium becomes richer for them (Carlson and Zmud, 1994). Put another way, as users gain experience with text-based CMC that is augmented with visualized typing data, they will learn how to encode and decode more expressive messages, and use it for more purposes.

These findings can also be extended to settings such as moderating an online discussion forum. While a moderator may not be able to review every single post, my findings will allow moderators to detect questionable postings. For example, if the typing patterns of the poster seem indicative of a personal opinion when it should be a fact, or extreme anger, this could raise a flag. The moderator could then review that post, or that user, more closely.

My thesis is concerned with human-to-human CMC, as opposed to human-to-computer CMC. While the findings from my thesis can eventually be applied to technologies such as automated assistants and chatbots, both of these introduce new variables, and thus fall outside the scope of my thesis.

1.2.6.2 Keystroke Research

Keystroke production is still a relatively understudied domain of language production, when compared to speech analysis and text analysis. Moreover, very few studies exist that investigate keystrokes in dialogue: most study keystrokes in monologue, or isolated settings such as writing essays or entering passwords (see Section 2.2.5 for a review of keystroke research in dialogues). Thus, these studies will help to expand the domain of keystroke research.

In addition, the web interface developed and used in my data collection (described in Section 4.4.3) is valuable for future researchers running task-based or interactive studies while simultaneously collecting detailed keystroke information. The code base for the interface is available in the same repository as the dataset corpus (https://github.com/angoodkind/KiDcorpus). Since the data is publicly available, it can be used to address numerous other questions about keystrokes and keystrokes in dialogue, e.g. related to demographics, power dynamics, or remote keystroke collection. As mentioned previously, not only is the amount of extant keystroke datasets small, but keystroke data from interactions is almost non-existent.[4] Thus, the research conducted for my thesis could also benefit future researchers who are investigating related questions.

[4] See https://vmonaco.com/datasets/ for a thorough list of available keystroke datasets.