Bots against incivility: Teaching receptive conversation skills using an NLP feedback algorithm

Burint Bevis ~~&~~ Michael Yeomans

Imperial College London

Keywords: natural language processing, technology adoption, conflict management

Abstract

This paper extends the research on technology-based interventions for helping individuals to manage difficult discussions by teaching individuals about key receptiveness features. It empirically tests the effectiveness of receiving immediate feedback from an NLP algorithm during a difficult discussion on being able to use receptive linguistic features. We developed an algorithm to detect key receptive features used in conversations. Based on what features the algorithm detects, it was able to recommend which features individuals should use more of, less of or keep going. We tested this algorithm in an experiment where participants were asked to write a response to points of view that they were strongly opposed to over multiple rounds. After each round, the algorithm identified areas for improvement and made suitable recommendations to the participant. We demonstrated that a personalised feedback approach worked well to not only increase receptiveness immediately post intervention, but also enable individuals to improve their skills over time. The results support the perspective that scalable, technology-based interventions can be effective, either as a complementary solution or potentially as a substitute for more traditional organisational training methods to train conversational skills. Unfortunately, participants reported that the feedback algorithm was more difficult to use than the receptiveness recipe, supporting the view that ease of use is a strong barrier to technology adoption.

1. Introduction

Disagreements are not only unpleasant, but between friends, family and colleagues, disagreements can ruin important relationships that end up spiraling out of control when left unchecked. The satisfaction of winning an argument may be short-lived and can come at the expense of important relationships in the long run. Unfortunately, conflict in the workplace may be inevitable for many people. Difficult discussion surrounding errors, differences in opinions on how to perform a task or even deep-rooted points of view on political politics and religion can spark discord between colleagues. These difficult discussions are further complicated by the lack of psychological safety in organisations (Edmondson, 1999). Employees fear that speaking up may be too costly, especially when communicating bad news to a superior (Cohen, 1958; Athanassiades, 1973; Roberts & O'Reilly, 1974; Jablin, 1982, Burke & Wilcox, 1969). When communicating bad news to superiors, employees may choose to avoid having difficult discussions altogether and stay silent (Tesser & Rosen, 1975). By doing so, employees feel that they can avoid any perceived negative repercussions that may befall them. While this strategy may mitigate negative risks for employees, it is likely to lead to negative consequences for the team and organisation as a whole. Fewer communications mean that decision-makers are unable to receive all the information necessary to make good decisions (Jehn, 1994, 1995; Amason, 1996) leading to a suboptimal performance at group (De Dreu and Weingart, 2003; Edmondson, 2004) and organisation level (Rawnsley, 1995; Lee, 1993). We want to help employees to engage more with their superiors and to encourage difficult discussions but in a manner where employees do not have to fear negative consequences from doing so. Other studies have shown that employees who choose to communicate bad news, adopt verbal strategies to enable a more receptive response (Lee, 1993). While it is not possible to know whether the efficacy and frequency of these verbal communication strategies are high enough, it is undoubtedly useful to try to increase the uptake of these verbal strategies in greater quantities as well as increasing their effectiveness.

A promising more modern approach to training is e-Learning (Narciss et. al., 2014). This has been shown to be effective in teaching new skills both in organisations and in adult education more generally but does come with some limitations (DeRouin, Fritzsche & Salas, 2005). In the modern workplace, the ability to work flexibly from various locations around the world means that employees may not be as concentrated in their working locations anymore. Technology aided learning and intelligent tutoring solutions are vital for skills building in a distributed virtual working environment. If the prevalence of remote working is expected to rise, the imperative of finding an effective solution sooner rather than later becomes more pressing.

For the task of training individuals in conversation skills, an algorithmic approach has been shown to work well in increasing receptiveness in the short term (Yeomans et. al., 2020). In that study, an algorithm was developed to understand common key linguistic features of receptiveness. Participants in this study were then provided with this recipe and were asked to respond as receptively as possible. The results showed that those who were given the recipe were able to use more receptiveness features than those who did not (Yeomans et. al., 2020). However, the effect seems to decay after the recipe was initially given to the participants in a study. The participants reported that the recipe was too complicated and intent to use was low (Yeomans et. al., 2020). Other studies have shown that providing immediate, personalised feedback helps to develop skills over time. Making the feedback timely, relevant and actionable was key to maximising the effectiveness of the feedback (Kehrer, Kelly & Heffernan, 2013; Clark & Mayer, 2003; Stoyanov & Kirchner, 2004).

We wish to aid workplace communications in the face of difficult discussions and help maintain healthy relationships. To do this, we need to better understand how to optimise interventions that will lead to better communications skills. The current body of literature focuses on the impact of communications in teams and organisations as well as the psychological mechanisms behind them. There are few empirical studies that test different interventions for building receptiveness skills, and fewer still on technology based interventions. Given the increased prevalence of remote working, understanding how to build soft skills without physical human presence is both important and interesting. This is what motivates our research. By testing the performance of our proposed personalised feedback algorithm rigorously, we hope to build on our understanding of how to design a more effective intervention policy. This leads us to our research question - “Can personalised feedback from an algorithm train individuals to use more receptive language more effectively than a set of instructions?”. Our results support the use of a personalised feedback algorithm.

We now review the literature on workplace communications & psychological safety, conflict management in organisations, error management training and the effectiveness of e-learning.

1.1. Workplace communications & psychological safety

It is acknowledged that psychological safety impacts communications within teams and organisations and is particularly pronounced in upward communications from subordinates to supervisors (Cohen, 1958; Athanassiades, 1973; Roberts & O’Reilly, 1974; Jablin, 1982, Burke & Wilcox, 1969). As highlighted by Edmondson (1999), individuals may perceive the cost of speaking up to outweigh the benefits for the speaker. This lack of psychological safety leads individuals to feel that they are unable to express themselves without the fear of reprisal in the form of “negative consequences of self-image, status or career” (Kahn, 1990). As such, psychological safety is a key enabler of communications and learning (Edmondson, 1999). These perceived costs are related to the speaker’s unwillingness to report errors due to feelings of embarrassment or the fear of reprisals in hospitals (Edmondson, 2004). Similar problems were found in other industries such as in financial services (Rawnsley, 1995; Lee, 1993). Studies of dyadic interactions have revealed that individuals have different threat sensitivity thresholds which determine whether they will react negatively to a potential threat (Tynan, 2005). This threat sensitivity has been shown to have a significant effect on upward communications. However, the task of better understanding these thresholds for each individual remains incomplete.

Individuals often respond to perceived threats of having to communicate bad news by avoiding that difficult discussion altogether e.g. the ‘MUM’ effect (Tesser & Rosen, 1975). Intuitively, it is not hard to understand why individuals do not wish to be the bearer of bad news. For empiricists, the challenge of gathering data on difficult discussions in the field when individuals tend to shy away from having those discussions in the first place presents an obstacle. Subordinates in large organisations were found to be less open in their communications with the supervisors than for communications from supervisors to subordinates (Jablin, 1982).

If an individual does decide to communicate bad news, the question then becomes one of how they communicate that news rather than if they communicate. When communicating bad news, individuals tend to use politeness strategies (Lee, 1993). Politeness was described as a key communication skill that is “basic to the production of social order, and a precondition of human cooperation” (Brown & Levinson, 1987). The use of politeness was found to vary according to gender and power that we know of. Men were more likely to adopt politeness strategies when the power difference between the speaker and the audience was large while this relationship was reversed for women (Lee, 1993). In the same study, individuals were shown to use politeness strategies under collectivistic rather than individualistic norms and that individuals who adopted more verbal strategies also communicated higher quality information and that that information was better received. Although gender and power were found to be two moderators for politeness strategy adoption, we still lack understanding of how individuals can recognise useful politeness strategies and develop the skills to implement them. Gaining a better understanding of strategy recognition and skills development should help decision-makers having to deal with the ‘MUM’ effect and encourage employees to communicate more frequently and effectively.

1.2. Conflict management in organisations

Workplace conflict can often be viewed as having a negative relationship with team effectiveness. Research by Jehn (1994, 1995) and Amason (1996) suggests that the quality of decision making in groups is reduced by relationship conflicts. De Dreu and Weingart (2003) found that relationship conflicts are negatively related to team effectiveness. Managing conflict takes time and effort. A study found that although dissent led to better decision-making, the time it took to arrive at that decision took twice as long (Schulz-Hardt et. al., 2006). Another study by De Dreu, Geibels, and Van de Vliert (1998) found that negotiators who tried to accommodate as many demands as possible took 30 per cent longer to reach an agreement than those who were more willing to compromise. The well-being of employees is another important factor. Those who perceive their superiors to be receptive to their point of view feel less emotionally exhausted (Lloyd, Boer, Keller & Voelpel, 2015). Other health and well-being benefits include less stress and feelings of burnout (Spector & Jex, 1998).

However, most of the literature view conflict as positively related to team performance and that a healthy level of disagreement is good for organisations (De Dreu, 2008; De Dreu & Van Vianen, 2001; Edmonson & Lei, 2014). Intuitively, more conflict is likely to be a result of greater engagement in difficult discussions between individuals with opposing views. Therefore a lack of engagement in difficult discussions means that critical information is not communicated, leading to suboptimal decision making. Not all conflicts should be treated the same. A closer investigation into workplace conflicts revealed that although task-related conflicts, which relates to conflicts over how a task or a job should be done, is more likely to be positively related to team performance than person-related conflicts, which relates to individuals and their values and personalities (De Dreu, 2008).

Causes of conflicts can come from difficult discussions. In the case of person-related conflicts, disagreement on issues such as politics and religion can produce strong reactions from both parties in a dyadic conversation (De Dreu, 2008). These include attempts to derogate the other person, among several other strategies, to gain a relative advantage over their perceived opponents in an attempt to win the argument (De Dreu, Weingart & Kwon, 2000; Tjosvold, 1991, 1998). By engaging in such actions, disagreements can harm relationships (Kennedy & Pronin, 2008; Weingart, Behfar, Bendersky, Todorova & Jehn, 2015) that are vital for performance and innovation in organisations.

1.3. Error management training

Interventions designed to reduce conflict range from those that aim to change individuals' beliefs (Schroder & Risen, 2016; Turner & Crisp, 2010) or encourage individuals to seek out opinions that strongly oppose their views (Bail et. al., 2018; Dorison, Minson & Rogers, 2019). Other strategies for learning in organisations, in general, were explored. A review by Carmeli & Gittell (2009) identified useful solutions. These include actively encountering problems (Cyert & March, 1963), examining past failures (Weick & Sutcliffe, 2001) and error management training (Keith & Frese, 2005).

Making errors is a recognised inevitability as well as a key part of ongoing learning. Training programs that have a focus on error management rather than error avoidance has been shown to be more effective (Chillarege, Nordstrom, & Williams, 2003; Keith & Frese, 2005; Nordstrom, Wendland & Williams, 1998; Yao, Wang, Yu, Guchait, 2019). In addition to enhanced performances, studies have shown that Error Management Training (EMT) reduces frustration and increases intrinsic motivation (Nordstrom, Wendland & Williams, 1998). In error management training, participants were encouraged to learn from their mistakes by being given the opportunity to make them (Keith & Frese, 2005). However, errors could lead to costly consequences for organisations and thus, employees are typically encouraged to avoid making any errors in the first place.

Proponents of EMT value errors as a means of providing valuable feedback as part of the learning process (Heimbeck, Frese, Sonnentag, & Keith, 2003). By exploring the psychological mechanisms behind the effectiveness of EMT, Frese & Keith (2005) suggest the error management training triggers self-regulation of emotions as well as self-regulation of cognitions. Self-regulation refers to processes "that enable an individual to guide his or her goal directed activities over time," comprising "modulation of thought, affect, behavior, or attention" (Keith & Frese, 2005; Karoly, 1993, p. 25). These psychological mechanisms do not appear to be evoked in error avoidance strategies. The self-regulation of control helps to manage negative emotions such as anxiety (Kanfer, Ackerman, & Heggestad, 1996), which in turn is linked to lower psychological safety (Edmondson, 1999). Removing negative emotions from the process is not the same as suppressing them. Suppressing emotions, in this case, can be draining and may lead to reduced cognitive abilities for other functions (Muraven & Baumeister, 2000).

EMT involves individuals being given a set of minimal instructions prior to starting a task and are then given the freedom to explore potential solutions to achieve their goals (Keith &

Frese, 2005). To understand whether a particular action has driven individuals towards a goal or further away from that goal, there needs to be an evaluative criterion that defines good or bad actions. Therefore, a key part of EMT is to identify actions that resulted in positive or negative outcomes and then to provide instructions to reduce the error rate (Dormann & Frese, 1994; Frese, 1995). Previous studies also demonstrate that these instructions must be brief, concise and frame instructions in a positive and constructive manner (Frese et al., 1991). When incorporating these instructions, EMT was shown to be more effective than an EMT approach without any feedback instructions or a pure error avoidance approach which utilizes instructions prior to the task (Heimbeck, Frese, Sonnentag, & Keith, 2003). This concept of learning through exploring different solutions and using the feedback from those experiences to inform future decisions is a familiar concept in machine learning known as reinforcement learning (Kaelbling, Littman & Moore, 1996). From experiments that aimed to teach agents to learn how to win in various games (typically classic Atari or strategy games such as chess), scholars have learnt that reinforcement learning works well when the long term rewards are important. Although the learning rate is low, learning is less likely to saturate quickly (Russell & Norvig, 2010). A successful learning outcome can be thought of as a reduction in the error rate over time.

1.4. Effectiveness of e-learning

A recent study showed that it was possible to use an algorithm to train individuals to respond in a way that was more receptive when conversing with someone who holds a strongly opposing view (Yeomans et. al., 2020). This intervention method presented a scalable solution to reducing conflict by providing a “receptiveness recipe” in an online setting to teach receptiveness skills without the aid of a human. According to DeRouin, Fritzsche & Salas (2005), “technology is the driving force of workplace training” in the modern workplace. E-learning covers a wide range of training methods that involve web-based applications, virtual classrooms, digital collaborations and other computer based learning as defined by the American Society for Training and Development (ASTD). While it is perhaps not surprising that e-learning is being used for technology skills building, e-learning has been extended to other types of skills. DeRouin, Fritzsche & Salas (2005) reported that Nestle used e-learning to build soft skills in communications, teamwork and communications skills (“Nestlé Widens Course Offers,” 2004) while another study revealed that Bank of America used e-learning to develop interpersonal skills training (Dobbs, 2000).

DeRouin, Fritzsche & Salas (2005) further argue that the effectiveness of using e-learning approaches to teaching soft skills is potentially limited. This is because soft skills require the development of verbal as well as visual communication skills typically developed face-to-face. One of the challenges with e-learning is the engagement of participants who require sustained self-motivation. However, this can be overcome by adopting a more natural conversation style that feels personal as part of the e-learning experience (Clark & Mayer, 2003). Other studies also highlight the value of personalised feedback as a feature of learning (Stoyanov & Kirchner, 2004). An advantage of web-based e-learning environments is the ability to implement personalised feedback which in itself can be adaptable for many users over time (Narciss et. al., 2014). As an example, in Hong Kong, there is an intelligent web-based tutoring system called SmartTutor which provides personalised feedback and suggestions for improvements (Cheung, Hui, Zhang, & Yiu, 2003). A separate review of personalised learning found that the students' profiles were also taken into account when recommending learning steps as part of many intelligent tutoring systems (Huang et. al., 2016). Aside from the content of recommendations, the effectiveness of the recommendation is higher when the feedback is immediate and occurs while the task is being completed rather than after the task has been completed (Kehrer, Kelly & Heffernan, 2013).

Different implementations will have different levels of success. The Technology Acceptance Model (TAM) predicted the users' acceptance of technology based on perceived ease of use and perceived usefulness (Venkatesh and Davis, 1996). The TAM shows that perceived ease of use and perceived usefulness is related to usage behaviour through behavioural intention which acts as a mediator. Later models attempt to explain the antecedence to perceived usefulness (Venkatesh & Davis, 2000) and perceived ease of use (Venkatesh and Bala, 2008) but does not affect the relationships between perceived usefulness, ease of use, intent to use and usage behaviour. Building upon research in this stream, the Unified Theory of Acceptance and Use of Technology (UTAUT) was developed (Venkatesh, Morris, Davis and Davis, 2003). The UTAUT model replaces perceived usefulness and ease of use with performance expectancy, effort expectancy, social influence and facilitation conditions. These four variables are again related to behavioural intention and usage behaviour as in the TAM, except that the relationships are also moderated by age, gender, experience and voluntariness of use.

1.5. Hypotheses

Providing instructions for how to write more receptive responses should lead to greater use of receptive features. However, over time, those instructions can be forgotten even with repeated practice. Therefore, being shown a set of instructions helps to increase the use of receptiveness features initially but those usage rates will decline without further interventions.

Hypothesis 1: Instruction based training for receptiveness will become less effective over time.

Teaching new skills effectively over a long period requires not only instructions at the beginning of the learning journey, but constant feedback and suggestions for improvement throughout the learning process. These improvement messages work best when they are positive and concise. In the case of helping individuals to manage disagreements and conflict in the workplace, providing regular feedback and suggestions for improvement should help increase the use of receptiveness features in conversations, especially when conversing with those who hold strongly opposing views.

Hypothesis 2: Personalised feedback based training increases the use of receptiveness features more than instruction based training.

We also expect that by incorporating feedback into the learning process, individuals would be able to estimate and measure their performance as they receive feedback over time. This should allow individuals to build upon the latest learnings rather than repeat the same lessons learnt previously. This leads us to our second hypothesis:

Hypothesis 3: The increased use of receptiveness features learned from personalised feedback messages is unlikely to decline over time.

Part of the condition for technology adoption is the perceived ease of use and perceived usefulness. As individuals do not need to retain a set of instructions and can rely on corrective feedback to manage errors we predict that it is more likely that interventions utilising personalised feedback messages will be easier to use and also therefore perceived as more useful than instruction based methods. This leads us to our third hypothesis.

Hypothesis 4: Individuals are more likely to use the personalised feedback approach as a method than instruction based training in future personal conflicts.

1.6. Overview of Present Research

We test the hypotheses by testing receptiveness interventions over time. We develop a new paradigm for measuring receptiveness across multiple conversations. In Study 1, we estimate the time course effect of a static "receptiveness recipe". We asked participants to write a response to opposing views over multiple rounds. Participants were randomly assigned to a Start and Middle condition. An algorithm was then used to estimate how receptive those statements were based on key receptiveness features for both conditions. The results showed that although the receptiveness recipe was initially successful in getting participants to use more receptiveness features, the usage rate declined over time.

In Study 2, we compare the receptiveness recipe to a dynamic, personalized feedback algorithm. In the feedback condition, participants were shown the feedback message based on their written response after each round. The recommendations in the feedback messages were generated dynamically based on the key receptiveness features detected from participants' responses. Our results showed substantial improvements in receptiveness feature usage over time in the feedback condition. Not only did we not see any decline in the use of receptive features, but we found that participants increased their use of these features over time. This is in contrast to the results in study 1.

2. Study 1

In our first study, we collect data on the time course of receptiveness over multiple conversations. Participants were randomly assigned to either the Start or Middle condition where they were asked to write a response to an opposing political view. In the Middle condition, participants were shown the receptiveness recipe after round 2 while in the Start condition, participants received the receptiveness recipe before the first round. After rounds 1 and 3, participants were asked a series of questions relating to trust, likelihood of adoption and difficulty of adoption. Using the response statements, we used an algorithm from a previous study to estimate how independent raters would have rated the receptiveness of each statement. Because the algorithm was proven to be able to predict receptiveness accurately, we were able to estimate receptiveness scores across multiple rounds without having to conduct a separate study using independent raters.

2.1 Study 1 Methods

2.1.1. Sample. All participants were recruited from Prolific to participate in a study on "how people interact with each other when discussing current 'hot-button' policy and social topics" (M_{age} = 35.9, 47.2% Male). We excluded participants who did not complete the attention checks or reported "no opinion" on their assigned issue, or who did not complete the study. This left a final sample size of 460 participants.

2.1.2. Protocol. Participants were shown an issue statement from one of the statements on sexual assault, women in STEM or police relations. Participants were then asked to state their agreement with the statement based on a scale from -3: strongly disagree to +3: strongly agree. The police relations statements were generated from a laboratory study of government employees who were interacting with a disagreeing peer over a chat platform. The statements on sexual assault and women in STEM were generated from a study on affective reactions to conflict using participants recruited on mTurk in an earlier study (Yeomans et al., 2020).

Based on the participants' stated positions., they were assigned to read a disagreeing text from the web service bank. Participants were randomly assigned one of two conditions - Start and Middle. In the Start condition, participants were shown the receptiveness recipe before round 1 (see Table 1). Participants were then shown an opposing political opinion and were asked to "Imagine that you are having an online conversation with this person. In your response, try to be as receptive and open-minded as you can". In the Middle condition, participants are asked to respond in the same manner. However, participants were not shown the receptiveness recipe until after round 2. The protocol is visualised in Figure 1.

After the first and final round, participants were asked questions regarding trust, technology adoption and difficulty of use. Finally, participants were asked to provide some basic demographic information including age, gender and political orientation. To score the receptiveness of each statement provided by the participants in each of the rounds, we applied the coefficients from a LASSO regression built in a previous study where a 20-fold nested cross-validation was utilized for accuracy and generalisability (Yeomans et. al., 2020). The LASSO regression was also validated against a set of receptiveness scores from a group of independent raters.

2.2 Study 1 Results

2.2.1. Receptiveness. Figure 2 shows the average receptiveness scores over time by condition. When participants were shown the receptiveness recipe, there was a significant increase in the use of receptiveness features. Receptiveness scores in rounds 1 & 2 for the Start condition were significantly higher than for rounds 1 & 2 in the Middle condition (β = .414, SE = 0.030, $t(919)$ = 13.723, $p < .001$). This proves that an algorithmic approach was successful in helping individuals to write more receptive responses.

Over time, the within-subject differences showed a decline in the receptiveness scores by participants ($\beta = -0.057$, $SE = 0.168$, $t(453) = 13.723$, $p < .001$) in the Start condition. This decline is further highlighted by comparing the receptiveness score of round 3 in the Start condition to those in the Middle condition. After round 3 in the Start condition, participants scored lower than participants who were exposed to the receptiveness recipe for the first time in the Middle condition ($\beta = -0.104$, $SE = 0.046$, $t(457) = -2.278$, $p = .023$). This suggests that the effects of being exposed to the receptiveness recipe is most effective immediately and will be less effective overtime without further intervention.

2.2.2. Receptiveness Features. The results from the overall receptiveness scores were mirrored in our analyses of the individual features. Changes in feature usage as a result of the receptiveness recipe should be significantly different between conditions in rounds 1 & 2. These features should also be significantly different from rounds 2 to round 3 within the Middle condition. The between-subjects differences by condition in feature use for rounds 1 & 2 are shown in Figure 3A. In the Start condition, participants used more features that had a positive relationship with receptiveness such as Agreement ($\beta = .519$, $SE = .044$, $t(919) = 11.753$, $p < .001$) and Acknowledgement ($\beta = .274$, $SE = .027$, $t(919) = 10.137$, $p < .001$) features. Participants also used fewer features that had a negative relationship with receptiveness such as Negation ($\beta = -0.310$, $SE = .097$, $t(919) = -3.192$, $p = .001$). The results suggest that participants were able to successfully follow instructions from the recipe.

We also compared within-subjects differences in feature use across rounds in the Middle condition shown in Figure 3B. We found that participants used significantly more Agreement ($\beta = .532$, $SE = .066$, $t(465) = 8.087$, $p < .001$) and Acknowledgement ($\beta = .328$, $SE = .039$, $t(465) = 8.387$, $p < .001$) features in round 3. However, there was less of a significant drop in round 3 for negatively related features such as Negation ($\beta = -0.170$, $SE = .145$, $t(465) = -1.172$, $p = .242$). The results suggest that it was easier to adopt more positively related features such as Agreement and Acknowledgement than to reduce negatively related features such as Negation, supporting the difference in feature usage found between the Start and Middle conditions in rounds 1 & 2. Figure 4 shows the average feature usage trend over time by condition. Figure 4 provides visual support that features such as Agreement and Acknowledgement appear to be successfully adopted as a result of participants being instructed to do so in the receptiveness recipe. The time course plots in Figure 4 also reveals a decline in usage rates for features such as Agreement ($\beta = -0.044$, $SE = .030$, $t(453) = -1.455$, $p = .146$) and Acknowledgement ($\beta = -0.035$, $SE = .020$, $t(453) = -1.750$, $p = .081$) in the Start condition. This suggests that learned skills through a one-off instruction is temporary. Without additional interventions, the long-term effect of the receptiveness recipe would decay.

2.2.3. Numeric Ratings. Participants reported a higher level of trust in the Middle condition after having been shown the receptiveness recipe ($\beta = .186$, $SE = .027$, $t(234) = 6.850$, $p < .001$). This result suggests that participants felt the receptiveness recipe would help their ability to respond receptively. However, the same participants did not report a higher likelihood of adopting the receptiveness recipe ($\beta = -0.044$, $SE = 0.052$, $t(234) = -0.852$, $p = .395$) and reported a lower ease of use rating ($\beta = .017$, $SE = 0.048$, $t(234) = .353$, $p = .724$).

Despite trusting the receptiveness recipe, there are other barriers to adopting this approach in the future.

2.3 Study 1 Discussion

The study was able to clearly show that individuals can adopt the use of receptiveness features when prompted to do so by a set of instructions. Participants used more features that had a positive relationship with receptiveness and fewer features that had a negative relationship with receptiveness in the start condition in rounds 1 & 2 compared to the middle condition. A similar expected result was found when comparing receptiveness feature usage from rounds 2 to 3 in the Middle condition. However, the usage rate declined over time in the Start condition when participants were no longer prompted to use any specific receptiveness features. Our results suggest that individuals need to be prompted to write receptive statements immediately prior to writing it each time. What was learnt about receptiveness does not seem to translate into long term behavioural changes. Therefore, it is important to consider how we can address learning over time where regular interventions are effective at sustaining or even increasing usage levels.

In addition, we discovered that although participants appear to trust the receptiveness recipe, it is surprising that participants did not report a higher willingness to adopt the recipe. Despite not reporting a particularly high likelihood of adoption, participants did adopt the receptiveness recipe in the short term. Perhaps the results suggest that individuals would be weary of the amount of continuous effort of having to read the recipe multiple times. Participants also reported that the receptiveness recipe was more difficult to use than having no instructions to follow. This is unsurprising as more effort is clearly required to follow any set of instructions than not.

3. Study 2

In Study 2, we build on the design of Study 1 to test a new form of intervention. In Study 1, we identified that showing individuals a set of instructions on how to be receptive does clearly work in encouraging individuals to use more receptiveness features. However, the results suggest that the intervention needs to be ongoing, provided immediately before use and enables individuals to evaluate their responses against the objective.

We build on the design of Study 1 to test whether providing real time feedback on writing receptiveness statements will help to fix the decline in receptiveness feature usage over time. Instead of a Start and Middle condition, participants will be randomly assigned to a generic and feedback condition (see Figure 5). The generic condition is almost identical to the start condition except with the following changes. Participants will be shown the receptiveness recipe before and after each round, with 4 rounds in total. In the feedback condition, participants will also be shown the receptiveness recipe prior to round 1 but will be subsequently shown a feedback message after each round. The feedback messages are intended to provide a way for participants to evaluate their feature usage in a timely manner. The feedback messages make suggestions to participants on which features to use more of, less of, or keep using the same amount of features. These feedback messages are specific to the previous text that the participants have written. We therefore have 2 conditions in Study 2, generic and feedback, where each participant will be shown either the receptiveness recipe or the feedback message after each round.

3.1. Developing the Feedback System

We wanted to give personalized feedback based on what each person writes. This requires a relatively sophisticated real-time NLP web service that will (a) parse the features of the text (in reasonable time), then (b) compare the counts of a subset of the most important features to an existing distribution of texts, then (c) produce actionable recommendations.

3.1.1. Feature Parsing. For this study, we developed a python programme analogous to the R politeness package (Yeomans et al., 2019). We needed to do this in Python to easily integrate the algorithm into the web service directly to allow participants to receive immediate feedback on the Qualtrics survey platform. Our main goal was to reproduce the algorithm, although as an additional benefit, we also improved some of the feature extraction, and these improvements are also now incorporated into the R package.

We decided to focus on a subset of 9 features that were particularly important based on evidence from an earlier study (Yeomans et al., 2020). Intuitively, it is not difficult to understand how agreement phrases such as ‘I agree’ or hedges such as ‘almost’ can help soften the tone in an otherwise potentially aggressive conversation. In the receptiveness recipe (Yeomans et al., 2020), ‘Impersonal Pronouns’ was found to be a very prominent feature. Upon closer inspection, ‘Impersonal Pronouns’ contain a lot of common words such as ‘that’, ‘this’, ‘it’, ‘other’, ‘things’. We decided to therefore remove impersonal pronouns from our list of key features to search for. In its place, we introduced ‘Subjectivity’ and ‘Adverb Limiter’. Subjective phrases such as ‘I think’, ‘we feel’ or ‘in my opinion’ can be considered phrases that help increase receptiveness. This feature was not incorporated in the original model (Yeomans et al., 2019) but is included in our feedback algorithm. Similarly, words such as ‘only’, ‘merely’ and ‘simple’ were had a negative relationship with receptiveness after some preliminary testing. This final list of 9 key features are 'Acknowledgement', 'Agreement', 'Hedges', 'Negation', 'Positive Emotion', 'Reasoning', ‘Subjectivity', 'Adverb Limiter', 'Second Person'.

3.1.2. Evaluation. To create personalized recommendations, we needed to establish benchmarks for “acceptable” use of each feature. We calculated these benchmarks using existing data collected in study 1. The thresholds are based on the distribution of features used among only people who were shown the receptiveness recipe. For each feature, the threshold was set to the median of the distribution. The thresholds were found to be the following for a given statement 100 words long: 0 Acknowledgement features, 1.1 Agreement features, 1.4 Hedges features, 1.4 Negation features, 2.9 Positive Emotion features, 0 Reasoning features, 0 Subjectivity features, 0 Adverb limiter features and 1.5 Second person features. See Appendix

C for each distribution and threshold. Intuitively, this means that most individuals do not use Acknowledgement features. For Positive Emotion phrases, individuals use this feature 2.9 times per 100 words on average. We use a binary decision rule to produce recommendations. For any feature, the number of features used may be above or below the threshold. These features can also either be positively or negatively related to receptiveness as identified in an earlier study (Yeomans et al., 2020). This gives us 4 feedback message types depending on whether the feature is expected to either increase or decrease receptiveness and if the feature count is above or below the threshold.

3.1.3. Actionable recommendations. For message type (1) when a feature is expected to be positively related to receptiveness and the feature count is above the threshold, the feedback will acknowledge that enough of the feature has been used and encourage the participant to carry on. For message type (2) when a feature is expected to be positively related to receptiveness and the feature count is below the threshold the feedback will acknowledge that the feature was not used enough and the participant will be encouraged to use more of this feature. For message type (3) when a feature is expected to be negatively related to receptiveness and the feature count is above the threshold, the feedback will acknowledge that too much of the feature has been used and encourage the participant to reduce their usage. For message type (4) when a feature is expected to be negatively related to receptiveness and the feature count is below the threshold, the feedback will acknowledge that the participant did not use too much of the feature and encourage the participant to continue. In Table 2, we show the 4 different types of feedback depending on the conditions.

As an example of the output from the algorithm, consider one of the responses to an opinion on a statement regarding women in STEM from a previous study:

“I understand your perspective and agree that I would not want to have resentment in the workplace against women, as that would further compound the issue we are looking at. I do think that it is true that women are underrepresented in STEM careers and am a believer that something should be done to address this discrepancy, even if that is not implementing a priority for women in hiring decisions. While I don't think that companies should explicitly hire simply because of their gender, I do think that they should be mindful of the gender gap in STEM and look to address those issues through their hiring practices.”

The algorithm detected 3 Hedges features, 3 Negation features, 2 Subjectivity features, 1 Reasoning feature, 1 Agreement feature, 1 Adverb Limiter feature and 1 Acknowledgement feature among others. The algorithm has acknowledged that 3 of the 9 features were used in sufficient quantities but has identified 6 features that could be used more/less to improve receptiveness. The feedback message presented back to the participant would be the below:

> *We showed your response to a text analysis algorithm that compared it to a large database of previous responses and identified 9 key linguistic features that are most likely to make your audience think you are more receptive. Here is the algorithm’s report, which has identified areas for improvement:*

- *The algorithm noticed you **used enough** acknowledgement phrases (e.g. "I understand" or "I get"). **Keep using these phrases** next time!*
- *The algorithm noticed you **did not use enough** agreement phrases (e.g. "I agree", "you are right"). **Use more of these phrases** next time! They will make you seem **more** receptive.*
- *The algorithm noticed you **used enough** hedging words (e.g. "almost" or "maybe"). **Keep using these phrases** next time!*
- *The algorithm noticed you used **too many** negation words (e.g. "did not", "would not"). Try to **decrease this** next time! They will make you seem **less** receptive.*
- *The algorithm noticed you **did not use enough** positive emotion words (e.g. "adore", "happy"). **Use more of these phrases** next time! They will make you seem **more** receptive.*
- *The algorithm noticed you used **too many** reasoning phrases (e.g. "therefore", "because"). Try to **decrease this** next time! They will make you seem **less** receptive.*
- *The algorithm noticed you **used enough** subjective phrases (e.g. "I believe" or "In my opinion"). **Keep using these phrases** next time!*
- *The algorithm noticed you used **too many** adverb limiters (e.g. "just", "only"). Try to **decrease this** next time! They will make you seem **less** receptive.*
- *The algorithm noticed you **used enough** second person phrases (e.g. "you" or "yourself"). **Keep using these phrases**!*

For a full list of possible feedback messages, see Appendix C. Our feedback algorithm was written in Python and was built as a web service deployed on Google App Engine. The web service was used to interact directly with Qualtrics to be able to provide immediate feedback to participants' responses. The Python programme relies on the SpaCy package as a key dependency. SpaCy was used to handle negations and other more complex NLP tasks. To interface with Qualtrics, we utilized the Python Flask package to receive and output text as JSON objects. The parameters for the App Engine were set to 1 CPU and 6 GBs RAM in a flexible environment. The code can be found here: https://github.com/bbevis/personalised_receptiveness

3.2. Study 2 Methods

3.2.1. Sample. All participants were recruited from Prolific to participate in a study on "how people interact with each other when discussing current 'hot-button' policy and social topics" (M_{age} = 33.5, 50.2% Male). We excluded participants who did not complete the attention checks or reported "no opinion" on their assigned issue, or who did not complete the study. This left a final sample size of 655 participants.

3.2.2. Protocol. Similarly to study 1, participants were shown an issue statement from one of the statements on sexual assault, women in STEM or police relations. Participants were then asked to state their agreement with the statement based on a scale from -3: strongly disagree to +3: strongly agree. The police relations statements were generated from a laboratory study of government employees who were interacting with a disagreeing peer over a chat platform. The statements on sexual assault and women in STEM were generated from a study on affective reactions to conflict using participants recruited on mTurk in an earlier study (Yeomans et al., 2020). Then, based on their agreement scores, they were assigned to read a disagreeing text from the web service bank. Next, participants were asked to "respond as they normally would in an online chat platform".

Participants were then shown the receptiveness recipe and were then randomly assigned one of two conditions - generic and feedback. The receptiveness recipe contains the 9 features that are known to impact receptiveness but do not contain an acknowledgement of their usage in the participants' response or suggestions for improvement. In the generic condition, participants were asked to "Imagine that you are having an online conversation with this person. In your response, try to be as receptive and open-minded as you can". In the feedback condition, participants are asked to respond in the same manner. However, instead of the receptiveness recipe, participants were shown a message from the feedback algorithm. The feedback consists of acknowledgement of whether participants used any of the key features known to improve receptiveness, as well as suggestions on how to improve the receptiveness for future responses. These feedback messages are generated by our feedback algorithm designed to provide actionable and tailored feedback based on each response. Overall, there are 4 rounds where participants were shown 4 different issue statements based on their opposing views. For both conditions, either the receptiveness recipe or the feedback message would be shown at the end of each round.

After the final round, participants were asked questions regarding relationship improvement, technology adoption, subjective learning and willingness to engage. See Appendix A for the list of questions. Finally, participants were asked to provide some basic demographic information including age, gender and political orientation. To score the receptiveness of each statement provided by the participants in each of the rounds, we applied the coefficients from a LASSO regression built in a previous study where a 20-fold nested cross-validation was utilized for accuracy and generalisability (Yeomans et. al., 2020). The LASSO regression was also validated against a set of receptiveness scores from a group of independent raters.

3.3. Study 2 Results

3.3.1. Receptiveness. Figure 6 shows the average receptiveness scores over time by condition. The increased receptiveness scores in the feedback condition confirm that our personalised feedback algorithm was successful in training individuals to use more receptiveness features. In round 1, all participants were initially asked to read the receptiveness recipe, identical to the recipe in study 1, before being asked to write a response to an opinion provided by another individual. In round 1, participants are shown the exact same receptive recipe as in Study 1. However, in this study, participants in both the generic condition and the feedback condition were asked to read the recipe first. In round 1, we found no statistically significant relationship between the conditions and receptiveness ($\beta = .010$, $SE = .040$, $t(653) = .298$, $p = .766$). Given that the conditions were identical in both conditions, these results are in line with expectations. In rounds 2 to 4 where participants in the feedback condition were given the personalised feedback messages and participants in the generic condition were still shown the receptiveness recipe, the differences in average receptiveness scores were far wider between the feedback and the generic conditions. We found a statistically significant relationship between the conditions and receptiveness ($\beta = .122$, $SE = .218$, $t(653) = .625$, $p < .001$). This proves that the personalised feedback messages were successful in helping individuals to use more receptive features than the receptiveness recipe, strongly supporting hypothesis 1.

The results showed that in the generic condition, the average receptive scores declined over time after initially being introduced to the receptiveness recipe in round 1. The findings are consistent with the results from study 1. Over time, the decline in receptiveness scores were significant in the generic condition ($\beta = -0.031$, $SE = .009$, $t(986) = -3.587$, $p < .001$). For hypothesis 2, we predicted that there would be little to no decay in the feedback condition. The results showed that not only did the average receptiveness scores not decline, but they improved over time. In round 2, the effect size was significant between the 2 conditions ($\beta = .081$, $SE = .039$, $t(653) = 2.110$, $p = .035$). In round 3, the effect size increased further ($\beta = .151$, $SE = .039$, $t(653) = 3.800$, $p < .001$). In round 4, the effect size was very similar to that of round 3 ($\beta = .149$, $SE = .039$, $t(653) = 3.8$, $p < .001$). The results exceeded our expectations and strongly supports hypothesis 2.

3.3.2. Receptiveness features. Figure 7 shows the average feature count per document for rounds 2 - 4 by condition. As shown in Figure 7, some features were used more frequently in the feedback condition than the generic condition. These include Agreement ($\beta = .181$, $SE = .058$, $t(653) = -3.122$, $p = .002$) and Acknowledgement ($\beta = .085$, $SE = .043$, $t(653) = 1.976$, $p = .005$) which are expected to have a positive effect on receptiveness. Other features such as Negation had lower usage rates in feedback condition as expected ($\beta = -0.159$, $SE = .094$, $t(653) = 1.677$, $p = .094$). Figure 8 shows the average feature usage trend over time by condition. In Figure 8, we can see that the use of Agreement features significantly increased from round 1 to round 2 in the feedback condition ($\beta = .191$, $SE = .049$, $t(328) = 3.894$, $p < .001$). Second Person features increase over time steadily over all rounds ($\beta = .110$, $SE = .026$, $t(986) = 4.182$, $p < .001$) in the feedback condition where the differences between the average feature use in round 4 was largest. Similarly, Acknowledgement feature usage increased gradually overtime ($\beta = .006$, $SE = .013$, $t(986) = 0.454$, $p = .650$) in the feedback condition where the largest difference in feature usage was in round 4. All of the features that had a higher feature usage rate in the feedback condition were features that are expected to have a positive relationship with receptiveness. These findings help explain the higher receptiveness scores for those in the feedback condition.

Also shown in Figure 8, 2 features had a lower usage rate in the feedback condition. This was the Negation ($\beta = -0.03$, $SE = .027$, $t(986) = -1.153$, $p = .249$) and adverb limiter phrases ($\beta = -0.045$, $SE = .011$, $t(986) = -3.872$, $p < .001$). Both features were expected to have a negative relationship with receptiveness. Therefore, a lower usage rate in the feedback condition meant that we would expect the receptiveness scores in the feedback condition to be even higher. All other key linguistic features were not found to have a significant effect.

3.3.3. Other Dependent Variables. The 4 additional dependent variables are Relationship Improvement, Subjective Learning, Technology Adoption and Willingness to Engage. For details on the scales and questions used for these variables see Appendix A. Checking internal consistency, we find that Technology Adoption (Cronbach's $\alpha = 0.47$) and Willingness to Engage (Cronbach's $\alpha = -1.4$) had very low values of alpha. Relationship improvement (Cronbach's $\alpha = 0.74$) and Subjective learning (Cronbach's $\alpha = 0.91$) had sufficiently high alpha values. Table 3 shows that the 2nd Technology Adoption scale has a negative relationship with the other scales for Technology Adoption. Similarly, the 2nd Willingness to Engage scale, which needed to be reversed, had a negative correlation with the 1st Willingness to Engage scale (corr = -0.42). This initially raises concerns over the reliability of the Technology Adoption and Willingness to Engage scales, which prompted us to investigate deeper.

Figure 9 shows the average difference between reported feelings on Technology Adoption, Subjective Learning, Relationship Improvement and Willingness to Engage. Figure 8 shows that there is a significant difference in Technology Adoption perception from participants between the two conditions ($\beta = -0.189$, $SE = .079$, $t(642) = -2.407$, $p = .016$). Checking each of the individual Technology Adoption scales, we found that participants felt that they are more likely to use the receptiveness recipe over the feedback algorithm in future personal conflicts ($\beta = -0.258$, $SE = .105$, $t(642) = -2.466$, $p = .014$). When asked how difficult it would be to use the receptiveness strategy learned in the study, participants felt that it would be easier to use the receptiveness recipe ($\beta = .402$, $SE = .134$, $t(642) = 3.015$, $p = .003$). There was no significant difference regarding whether participants were prepared to practice using the materials learned from this study ($\beta = .060$, $SE = .141$, $t(642) = .427$, $p = .670$). Lastly, there was a small effect size on whether participants are willing to try to use the strategies learned in this study in future conflicts ($\beta = .242$, $SE = .110$, $t(642) = 2.202$, $p = .028$). The results suggest that participants found the receptiveness recipe easier to use and that they were less likely to use the feedback algorithm in future personal conflicts.

For the Willingness to Engage scale, participants felt that they were just as likely to use use the feedback algorithm to the receptiveness recipe when engaging in future difficult discussions ($\beta = .016$, $SE = .079$, $t(645) = -0.199$, $p = .842$). Finally, for the dependent variables with high Cronbach's alphas, we were not able to find a significant effect size. Participants did not feel that the feedback algorithm helped them to learn sufficiently more about receptiveness than the receptiveness recipe ($\beta = .045$, $SE = .078$, $t(643) = .578$, $p = .564$), nor did they feel that the feedback algorithm will ultimately help manage future relationships in the face of difficult discussions more than the receptiveness recipe ($\beta = .025$, $SE = .078$, $t(643) = .324$, $p = .746$).

4. General Discussion

When left unchecked, disagreements can ruin relationships between friends, family and colleagues. But avoiding disagreement can be just as costly, when true differences in values and beliefs are left unaddressed and allowed to persist below the surface. As a consequence, scholars have tried to understand interventions individuals can adopt to increase the effectiveness of their conversational strategies when discussing difficult issues. But it can be difficult to help people change their behavior in the heat of the moment, when a disagreement captures their attention. And this behavior change can be particularly hard to sustain over time.

In this paper, we extend this line of research by investigating strategies for improving conversational receptiveness over time. In our studies, we create a practice space for conversational conflict, by having participants write responses to multiple opposing views, in sequence. In Study 1, we show that while a static instructional intervention (the "recipe") can improve receptiveness initially, that improvement fades somewhat over multiple conversations. In Study 2, we compared the static intervention to a dynamic, personalised feedback system. For this system, we developed an algorithm that can detect key linguistic features and recommend which features should be utilised more frequently, less frequently or maintain frequency. We show that the feedback system has the opposite effect over time, improving receptiveness in subsequent rounds, over and above the initial baseline set by the static intervention. This was consistent with our hypotheses: our responsive feedback system was more successful in increasing the use of receptive features for longer.

4.1. Theoretical contributions.

This research contributes to the literature on teaching conversation skills through the use of technology interventions. Most studies focused on understanding the psychological mechanisms and impact of poor communication in teams and organisations. We build directly on the research done on training receptiveness skills (Yeomans et. al., 2020). Our studies show that future intervention designs should incorporate personalised feedback for increased effectiveness where these personalised feedbacks are timely, concise and positive.

We found that the use of receptiveness features increased significantly when using the feedback algorithm. Participants reported that they were not more likely to adopt the feedback algorithm in a real world future personal conflict and found it more difficult to use than the receptiveness recipe. We were also not able to find a significant effect on our other dependent variables either. According to the Technology Acceptance Model (TAM) (Venkatesh and Davis, 1996; Venkatesh & Davis, 2000; Venkatesh and Bala, 2008) usage intent is influenced by ease of use and perceived usefulness. Our results suggest that the ease of use in the TAM was the cause for the lack of usage intent. The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis and Davis, 2003) does imply that the 4 conditions of performance expectancy, effort expectancy, social influence and facilitation conditions moderated by age, gender, experience and voluntariness of use may be a more robust model.

Given the minimal effort and a randomised mix of age, gender, experience and voluntariness of use, we can rule out the effect of the moderators on user intent as given by the UTAUT model.

4.2. Limitations of the current data.

In this study, we focussed on written communication from one individual to a predefined set of issue statements. There are four main limitations with this study that we can identify. a) There is no pre-existing relationship between the people writing to one another. b) We have only assessed written communication skills and have not included any other forms of communication. c) The topics that can be discussed are limited within the scope of this study. d) The individuals are exposed to deep-seated political and social issues that are more related to personal views rather than issues related to tasks or topics discussed typically in an organization.

The ultimate goal of increasing receptiveness skills is to help individuals maintain a healthy working relationship while providing them with the skills to communicate contentious points of view to those they may fear a negative outcome from. However, the effectiveness of an intervention policy may well rely on the context of the relationship. Some relationships may have a higher threshold for acceptable levels of disagreement than others. In this study, it is not possible to take into account the context of the relationship. Power, attractiveness, strength of ties are all known to be moderators of communications.

Verbal communications differ from written communications in two ways. When writing a response, individuals can be much more considered and nuanced in their response. There is less risk for impulsive reactions when the respondents can take the time to compose a more measured and thoughtful response. Secondly, individuals communicate with more than just words. Facial expressions, body language and eye contact can potentially transmit more receptive cues than written words.

The issue statements that participants were asked to respond to were based on three topics - Black Lives Matter, Sexual Assault on Campus and ISIS. These issues are hot topics but perhaps not as current as they could have been. At the time of this experiment, the world had already gone through a year of tough restrictions due to COVID-19 and perhaps some of the participants do not hold such strong opinions as they once did on each of our three topics (ISIS in particular). Although the number of issues themselves is naturally limiting in an experiment, using the most relevant topics could impact the effect sizes.

Lastly, the topics discussed are perhaps more likely to be discussed in anonymous online forums and other more private settings. Understanding how individuals converse in the workplace over hotly disputed topics may perhaps allow us to tailor the algorithm to extract more relevant features and therefore make more meaningful recommendations. These topics might include pay and remuneration, ethics, diversity, sustainability, technology, and burnout. The objective of pay negotiations might be to come to a happy compromise for all individuals involved in the discussion. With topics such as Black Lives Matter in an anonymous online forum, individuals may use more aggressive language with less care about the outcome of the discussion. Individuals may also perceive their ability to get away with being less receptive to be higher and may respond differently to either of our intervention strategies.

4.3. Future directions.

The results of our study showed a strong effect size for the feedback condition. While great care was taken to ensure that the two conditions were as close to each other as possible and that participants were randomly placed into either of the conditions, there were naturally some differences in the format of the way participants received the feedback messages compared to how the receptiveness recipe was structured. Therefore, a simple experiment for next time could repeat this experiment but in one condition, randomise the 'feedback' messages such that some would be wrong and some would be right and in the other condition, the feedback messages are the same as in this study. This should eliminate any potential effects of the different formats between the receptiveness recipe and the feedback algorithm.

So far, these studies have focussed on written communication. There is potential to go further and attempt to understand how individuals communicate verbally during disagreements and develop an intervention based on linguistic cues found in verbal disagreements. Natural Language Processing has come a long way, with open-sourced code now available to perform the text to speech processing and back again. An experiment could be conducted using a similar protocol, but instead of participants interacting with written text, they could be asked to listen to an audio message and then asked to respond verbally. This could help scholars understand more about how individuals respond to strongly opposing views with less consideration time and in a more natural conversational environment. This may also provide new approaches to conduct experiments in other areas of speech and language research.

Lastly, as this study was conducted as an experiment, testing this algorithm in a field setting would be a useful next step. If possible, and without breaching any data privacy rules, communications between employees via email and instant messaging can potentially be used to better identify key receptive linguistic features in disagreements in the workplace. Although it does not take into account any verbal disagreements, we may have a higher chance of capturing linguistic features in a more relevant context. In addition, we may be able to better understand more about adopting a feedback algorithm in a real world setting and how disruptive such a technology might be. This last point is an important topic to explore if an intervention is to be effective.

5. Conclusion

The way individuals communicate with each other affects not only those individuals but organisations as a whole depend on frequent and good quality information being relayed at the relevant time. This research has empirically demonstrated that a feedback algorithm can help individuals to adopt receptive linguistic features robustly. By following the feedback given by the algorithm, individuals have managed to increase the receptiveness of their responses by only changing the use rate of 5 key features - agreement, acknowledgement, subjectivity, second person phrases and negation phrase. This proves that a simple algorithmic-based intervention centred on being able to respond dynamically can be effective. There are exciting future research opportunities involving verbal feedback and field experiments.

6. References

Abbas, R. Z., Murad, H. S., Yazdani, N., & Asghar, A. (2014). Extending “Kahn’s model of personal engagement and disengagement at work” with reference to existential attributes: A case study of HR managers in Pakistan. *International Journal of Social Economics*, *41*(1), 2–31. https://doi.org/10.1108/IJSE-10-2012-0143

Amason, A. C. (1996). Distinguishing the Effects of Functional and Dysfunctional Conflict on Strategic Decision Making : Resolving a Paradox for Top Management Teams. *The Academy of Management Journal*, *39*(1), 123–148. https://doi.org/10.2307/256633

Athanassiades, J. (1973). The Distortion of Upward Communication in Hierarchical Organizations. *The Academy of Management Journal*, 16(2), 207-226. https://doi.org/10.2307/255323

Brown, P. & Levinson, S. C., (1987). Politeness: Some universals in language usage (Vol. 4). *Cambridge university press*. https://doi.org/10.1017/cbo9780511813085

Burke, R. J., & Wilcox, D. S. (1969). Effects of Different Patterns and Degrees of Openness in Superior-Subordinate Communication on Subordinate Job Satisfaction. *Academy of Management Journal*, *12*(3), 319–326. https://doi.org/10.5465/255179

Carmeli, A., & Gittell, J. H. (2009). High-quality relationships, psychological safety, and learning from failures in work organizations. *Journal of Organizational Behavior*, *30*(6), 709–729. https://doi.org/10.1002/job.56

Cheung, B., Hui, L., Zhang, J., & Yiu, S. M. (2003). SmartTutor: An intelligent tutoring system in web-based adult education. *Journal of Systems and Software*, *68*(1), 11–25. https://doi.org/10.1016/S0164-1212(02)00133-4

Chillarege, K. A., Nordstrom, C. R., & Williams, K. B. (2003). Learning from our mistakes: Error management training for mature learners. *Journal of Business and Psychology, 17*(3), 369–385. https://doi.org/10.1023/A:1022864324988

Cohen, A. R. (1958). Upward Communication in Experimentally Created Hierarchies. *Human Relations*. 11(1):41-53. https://doi.org/10.1177/001872675801100103

Cyert, R. M., & March, J. G. (1963). *A behavioral theory of the firm* (Vol. 2, No. 4, pp. 169-187). https://doi.org/10.2307/2091213

De Dreu, C. K. W., Giebels, E., & Van de Vliert, E. (1998). Social motives and trust in integrative negotiation: The disruptive effects of punitive capability. *Journal of Applied Psychology, 83*(3), 408–422. https://doi.org/10.1037/0021-9010.83.3.408

De Dreu, C. K. W., Weingart, L. R., & Kwon, S. (2000). Influence of social motives on integrative negotiation: A meta-analytic review and test of two theories. *Journal of Personality and Social Psychology, 78*(5), 889–905. https://doi.org/10.1037/0022-3514.78.5.889

De Dreu, C. K. W., & Van Vianen, A. E. M. (2001). Managing relationship conflict and the effectiveness of organizational teams. *Journal of Organizational Behavior*, *22*(3), 309–328. https://doi.org/10.1002/job.71

De Dreu, C. (2008). The virtue and vice of workplace conflict: food for (pessimistic) thought. *Journal of Organizational Behavior*, *29*(1), 5–18. https://doi.org/10.1002/job.474

DeRouin, R. E., Fritzsche, B. A., & Salas, E. (2005). E-learning in organizations. *Journal of Management*, *31*(6), 920–940. https://doi.org/10.1177/0149206305279815

De Dreu, C. K., & Weingart, L. R. (2003). Task versus relationship conflict, team member satisfaction, and team effectiveness: A meta-analysis. *Journal of Applied Psychology*, *88*(4), 741-749. https://doi.org/10.1037/0021-9010.88.4.741

Dobbs, K. (2000). What the Online World Needs Now: Quality. *Training*, *37*(9), 84. https://doi.org/10.1177/0149206305279815

Dormann, T., & Frese, M. (1994). Error training: Replication and the function of exploratory behavior. *International Journal of Human-Computer Interaction*, *6*(4), 365-372. https://doi.org/10.1080/10447319409526101

Edmondson, A. (1999). Psychological safety and learning behavior in work teams. *Administrative Science Quarterly*, *44*(2), 350–383. https://doi.org/10.2307/2666999

Edmondson, A. C. (2004). Learning from Mistakes is Easier Said than Done: Group and Organizational Influences on the Detection and Correction of Human Error. *The Journal of Applied Behavioral Science*, *40*(1), 66–90. https://doi.org/10.1177/0021886304263849

Edmondson, A. C., & Lei, Z. (2014). Psychological Safety: The History, Renaissance, and Future of an Interpersonal Construct. *Annual Review of Organizational Psychology and Organizational Behavior*, *1*, 23–43. https://doi.org/10.1146/annurev-orgpsych-031413-091305

Frese, M., Brodbeck, F., Heinbokel, T., Mooser, C., Schleiffenbaum, E., & Thiemann, P. (1991). Errors in training computer skills: On the positive function of errors. *Human-Computer Interaction*, *6*(1), 77-93. https://doi.org/10.1207/s15327051hci0601_3

Frese, M. (1995). Error management in training: Conceptual and empirical results. In *Organizational learning and technological change* (pp. 112-124). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-79550-3_7

Heimbeck, D., Frese, M., Sonnentag, S., & Keith, N. (2003). Integrating errors into the training process: The function of error management instructions and the role of goal orientation. *Personnel Psychology*, 56, 333–361. https://doi.org/10.1111/j.1744-6570.2003.tb00153.x

Huang, X., Craig, S. D., Xie, J., Graesser, A., & Hu, X. (2016). Intelligent tutoring systems work as a math gap reducer in 6th grade after-school program. *Learning and Individual Differences*, *47*, 258–265. https://doi.org/10.1016/j.lindif.2016.01.012

Jablin, F. M. (1982), Formal structural characteristics of organizations and superior-subordinate communication. *Human Communication Research*, 8: 338-347. https://doi.org/10.1111/j.1468-2958.1982.tb00672.x

Jehn, K. A. (1994). Enhancing effectiveness: An investigation of advantages and disadvantages of value-based intragroup conflict. *International journal of conflict management*. 5(3), 223-238. https://doi.org/10.1108/eb022744

Jehn, K. A. (1995). A Multimethod Examination of the Benefits and Detriments of Intragroup Conflict. *Administrative Science Quarterly*, *40*(2), 256–282. https://doi.org/10.2307/2393638

Kaelbling, L. P., Littman, M. L., & Moore, A. W. (1996). Reinforcement learning: A survey. *Journal of artificial intelligence research*, *4*, 237-285. https://doi.org/10.1613/jair.301

Kahn, W. A. (1990). Psychological conditions of personal engagement and disengagement at work. *Academy of Management Journal*, *33*(4), 692–724. https://doi.org/10.5465/256287

Kanfer, R., Ackerman, P. L., & Heggestad, E. D. (1996). Motivational skills & self-regulation for learning: A trait perspective. Learning and individual differences, 8(3), 185-209. https://doi.org/10.1016/s1041-6080(96)90014-x

Karoly, P. (1993). Mechanisms of self-regulation: A systems view. *Annual review of psychology*, *44*(1), 23-52. https://doi.org/10.1146/annurev.ps.44.020193.000323

Kehrer, P., Kelly, K., & Heffernan, N. (2013). Does immediate feedback while doing homework improve learning? *FLAIRS 2013 - Proceedings of the 26th International Florida Artificial Intelligence Research Society Conference*, 542–545.

Kennedy, K. A., & Pronin, E. (2008). When disagreement gets ugly: Perceptions of bias and the escalation of conflict. *Personality and Social Psychology Bulletin*, *34*(6), 833-848. https://doi.org/10.1177/0146167208315158

Keith, N., & Frese, M. (2005). Self-regulation in error management training: emotion control and metacognition as mediators of performance effects. *Journal of Applied Psychology*, *90*(4), 677. https://doi.org/10.1037/0021-9010.90.4.677

Lee, F. (1993), Being Polite and Keeping MUM: How Bad News is Communicated in Organizational Hierarchies1. *Journal of Applied Social Psychology*, 23: 1124-1149. https://doi.org/10.1111/j.1559-1816.1993.tb01025.x

Lee, F. (1999). Verbal strategies for seeking help in organizations 1. *Journal of Applied Social Psychology*, *29*(7), 1472–1496. https://doi.org/10.1111/j.1559-1816.1999.tb00148.x

Lloyd, K. J., Boer, D., Keller, J. W., & Voelpel, S. (2015). Is my boss really listening to me? The impact of perceived supervisor listening on emotional exhaustion, turnover intention, and organizational citizenship behavior. *Journal of Business Ethics*, *130*(3), 509-524. https://doi.org/10.1007/s10551-014-2242-4

Mayer, R. E., & Clark, R. (2003). The promise of educational psychology (vol II): Teaching for meaningful learning. 10.1002/pfi.4930420410

Muraven, M., & Baumeister, R. F. (2000). Self-regulation and depletion of limited resources: Does self-control resemble a muscle?. *Psychological bulletin*, *126*(2), 247. https://doi.org/10.1037/0033-2909.126.2.247

Narciss, S., Sosnovsky, S., Schnaubert, L., Andrès, E., Eichelmann, A., Goguadze, G., & Melis, E. (2014). Exploring feedback and student characteristics relevant for personalizing feedback strategies. *Computers and Education*, *71*, 56–76. https://doi.org/10.1016/j.compedu.2013.09.011

Nestlé widens course offers for all its staff. 2004. IT Training, May: 11.

Nordstrom, C., Wendland, D., & Williams, K. (1998). "To Err Is Human": An Examination of the Effectiveness of Error Management Training. *Journal of Business and Psychology, 12*(3), 269-282. https://doi.org/10.1037/0021-9010.93.1.59

Rawnsley, J. H. (1996). Total risk: Nick Leeson and the fall of Barings Bank. HarperCollins.

Roberts, K. H., & O'Reilly, C. A. (1974). Failures in Upward Communication in Organizations: Three Possible Culprits. *Academy of Management Journal*, *17*(2), 205–215. https://doi.org/10.5465/254974

Schulz-Hardt, S., Brodbeck, F. C., Mojzisch, A., Kerschreiter, R., & Frey, D. (2006). Group decision making in hidden profile situations: dissent as a facilitator for decision quality. *Journal of personality and social psychology*, *91*(6), 1080. https://doi.org/10.1037/0022-3514.91.6.1080

Spector, P. E., & Jex, S. M. (1998). Development of four self-report measures of job stressors and strain: interpersonal conflict at work scale, organizational constraints scale, quantitative workload inventory, and physical symptoms inventory. *Journal of occupational health psychology*, *3*(4), 356. https://doi.org/10.1037/1076-8998.3.4.356

Stoyanov, S., & Kirchner, P. (2004). Expert concept mapping method for defining the characteristics of adaptive e-learning: ALFANET project case. *Educational technology research and development*, *52*(2), 41-54. 10.1007/BF02504838

Tesser, A., Rosen, S. (1975). The Reluctance to Transmit Bad News. *Advances in Experimental Social Psychology* (Vol. 8, pp. 193–232). https://doi.org/10.1016/S0065-2601(08)60251-8

Tjosvold, D. (1991). Rights and responsibilities of dissent: Cooperative conflict. *Employee Responsibilities and Rights Journal*, *4*(1), 13-23. 10.1007/BF01390435

Tjosvold, D. (1998). Cooperative and competitive goal approach to conflict: Accomplishments and challenges. *Applied Psychology*, *47*(3), 285-313. 10.1111/j.1464-0597.1998.tb00025.x

Tynan, R. (2005). The effects of threat sensitivity and face giving on dyadic psychological safety and upward communication. *Journal of Applied Social Psychology*, *35*(2), 223–247. https://doi.org/10.1111/j.1559-1816.2005.tb02119.x

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences*, *39*(2), 273-315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision sciences*, *27*(3), 451-481. https://doi.org/10.1111/j.1540-5915.1996.tb00860.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), 186-204. https://doi.org/10.2307/30036540

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478. https://doi.org/10.2307/30036540

Weick, K. E., & Sutcliffe, K. M. (2001). Managing the unexpected: Assuring high performance in an age of complexity. *Jossey-Bass.*

Weingart, L. R., Behfar, K. J., Bendersky, C., Todorova, G., & Jehn, K. A. (2015). The directness and oppositional intensity of conflict expression. *Academy of Management Review*, *40*(2), 235-262. https://doi.org/10.5465/amr.2013-0124

Yao, S., Wang, X., Yu, H., & Guchait, P. (2019). Effectiveness of error management training in the hospitality industry: Impact on perceived fairness and service recovery performance.

International Journal of Hospitality Management, 79, 78–88. https://doi.org/10.1016/j.ijhm.2018.12.009

Yeomans, M., Kantor, A., & Tingley, D. (2019). The politeness package: Detecting politeness in natural language. *R Journal*, *10*(2), 489–502. https://doi.org/10.32614/RJ-2018-079

Yeomans, M., Minson, J., Collins, H., Chen, F., & Gino, F. (2020). Conversational receptiveness: Improving engagement with opposing views. *Organizational Behavior and Human Decision Processes*, *160*, 131–148. https://doi.org/10.1016/j.obhdp.2020.03.011

Figures & Tables

Table 1. The receptiveness recipe intervention from studies 1& 2. The recipe is a fixed set of instructions designed to teach receptiveness skills as shown below.

On the next page, you will see another statement from a different person, along with an open-ended text box, and you will write another response to that new person. **In writing your response, try as hard as possible to signal receptiveness by using** the strategies you learned about earlier in this survey.

Remember, the following four strategies have been identified as signalling receptiveness in our previous research:

Actively acknowledge the other perspective. For example: "I understand that...," or " I see your point", or "What I think you are saying is ..." Acknowledging helps to show that you've been listening

Hedge your claims. Say "I think it's possible that..." rather than "This will happen because..." Others appreciate hedging because it sounds less dogmatic. Avoid reciting explanations or facts, which can sound argumentative and condescending. And don't suggest things are so obvious - avoid words like "just", "simply", or "only".

Phrase arguments in positive versus negative terms. "I think it's helpful to maintain a social distance" vs. "You should not be socializing right now." Don't contradict the perspectives or beliefs of others.

Highlight areas of agreement, no matter how small or obvious. For example, "I agree that..." Or "you're right about" Even when people passionately disagree, they usually have some shared values or common beliefs.

Table 2. Description of possible feedback messages from Study 2. Some features had either positive (e.g. acknowledgement) or negative (e.g. negation) effects on receptiveness, requiring different phrasing. Additionally, messages varied based on whether the participant had crossed the usage threshold for that feature in their previous message.

	Above threshold	**Below threshold**
Positive impact on receptiveness	<u>Feedback condition 1</u> • Acknowledges **enough** was used • Recommends to **continue**	<u>Feedback condition 2</u> • Acknowledges **not enough** use was used • Recommends using **more**
Negative impact on receptiveness	<u>Feedback condition 3</u> • Acknowledges **too much** was used • Recommends to **reduce**	<u>Feedback condition 4</u> • Acknowledges **not too much** was used • Recommends to **continue**

Table 3. Correlation matrix of Technology Adoption questions.TechAdopt_2 relates to the question on the perceived difficulty of usage of the receptiveness strategy for future uses.

	TechAdopt_1	TechAdopt_2	TechAdopt_3	TechAdopt_4
TechAdopt_1	1	-0.33	0.49	0.8
TechAdopt_2	-0.33	1	-0.04	-0.27
TechAdopt_3	0.49	-0.04	1	0.58
TechAdopt_4	0.8	-0.27	0.58	1

Figure 1. Flow chart depicting the protocol steps for original study.

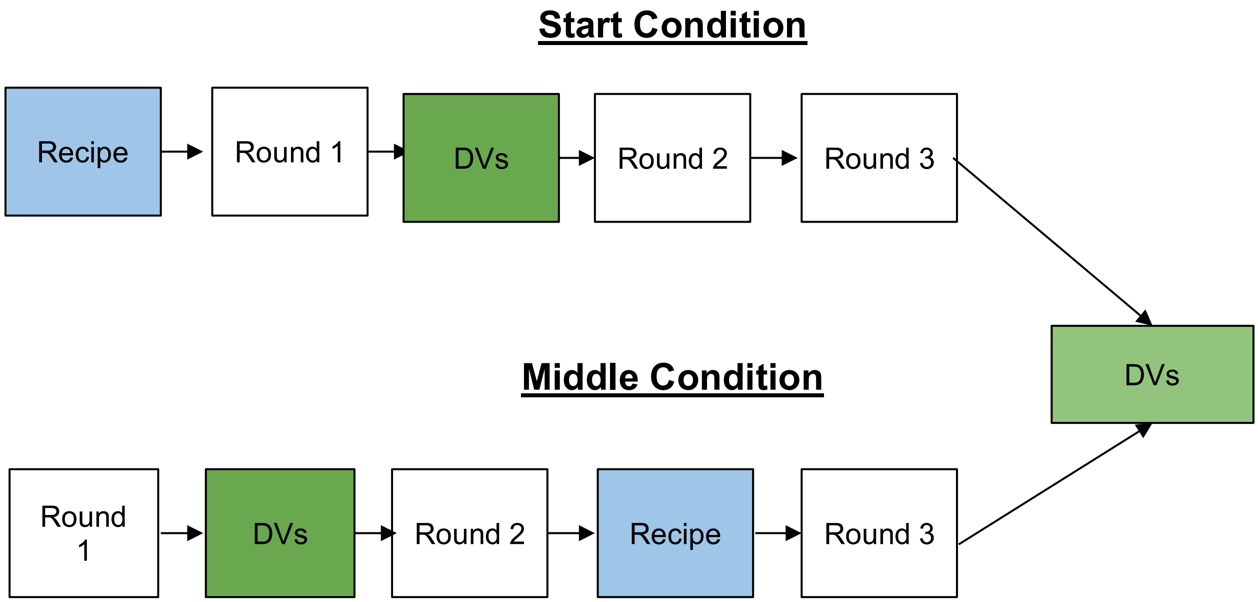


Figure 2. Comparing average receptiveness scores by round and by condition for study 1. Each data point represents a group mean as a percentile and their corresponding 95% confidence interval.

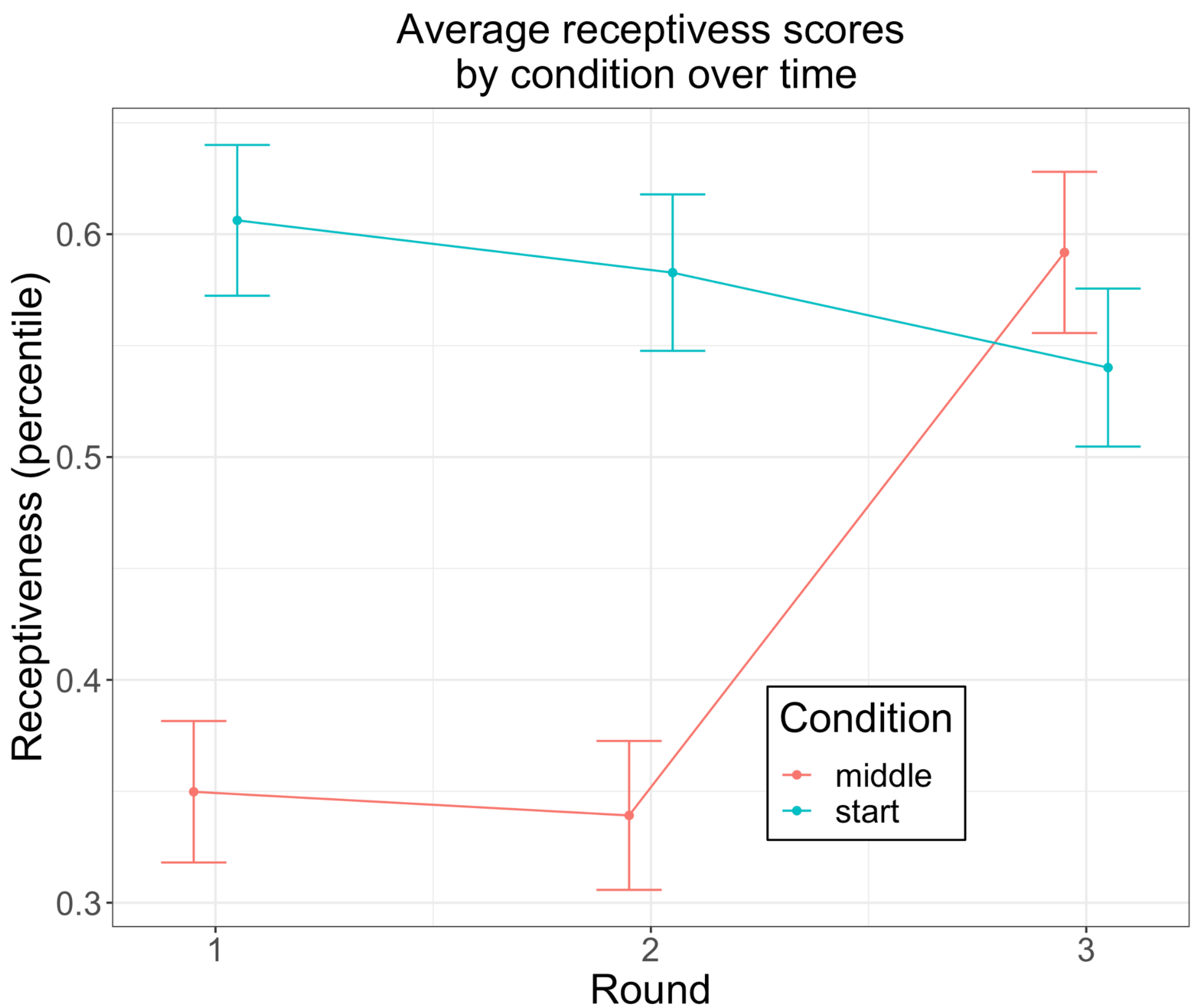


Figure 3. Changes in features use in Study 1. Figure 3A compares the average feature usage per document for each of the key receptiveness features by condition in rounds 1 & 2. Figure 3B compares the average feature usage per document for each of the key receptiveness features in the Middle condition between round 2 and round 3. Each data point shows the average feature count per document and their corresponding 95% confidence intervals.

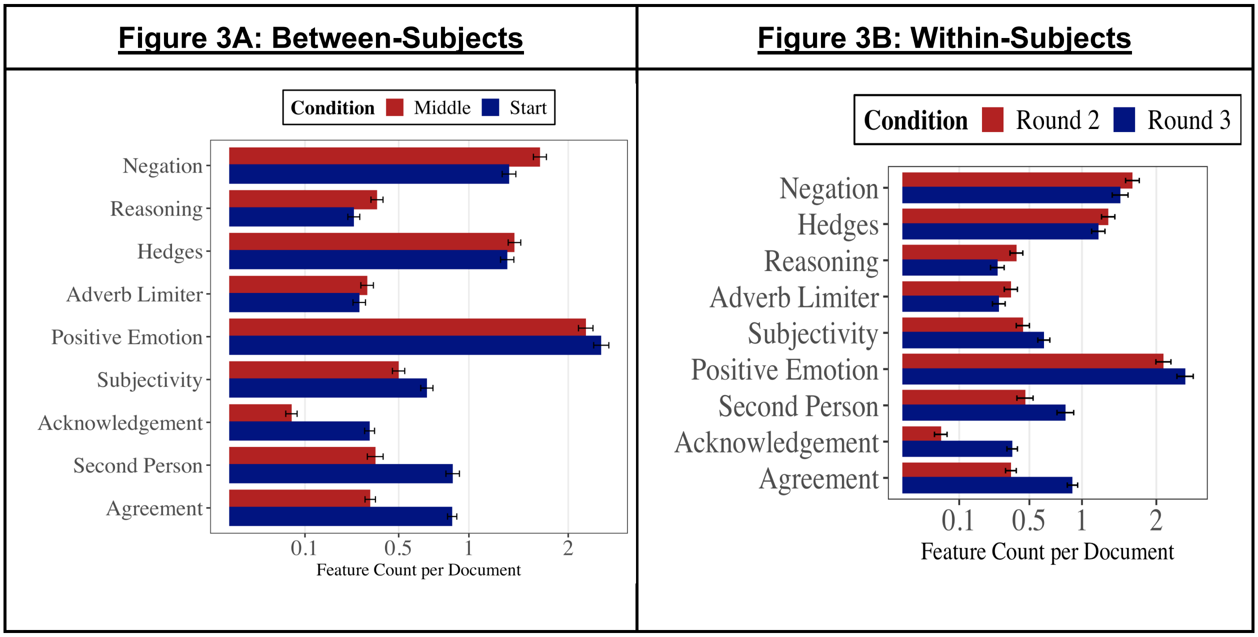


Figure 4. Comparing feature usage trends over time by key feature and condition for Study 1. Each data point represents the average feature use per document and their corresponding 95% confidence interval.

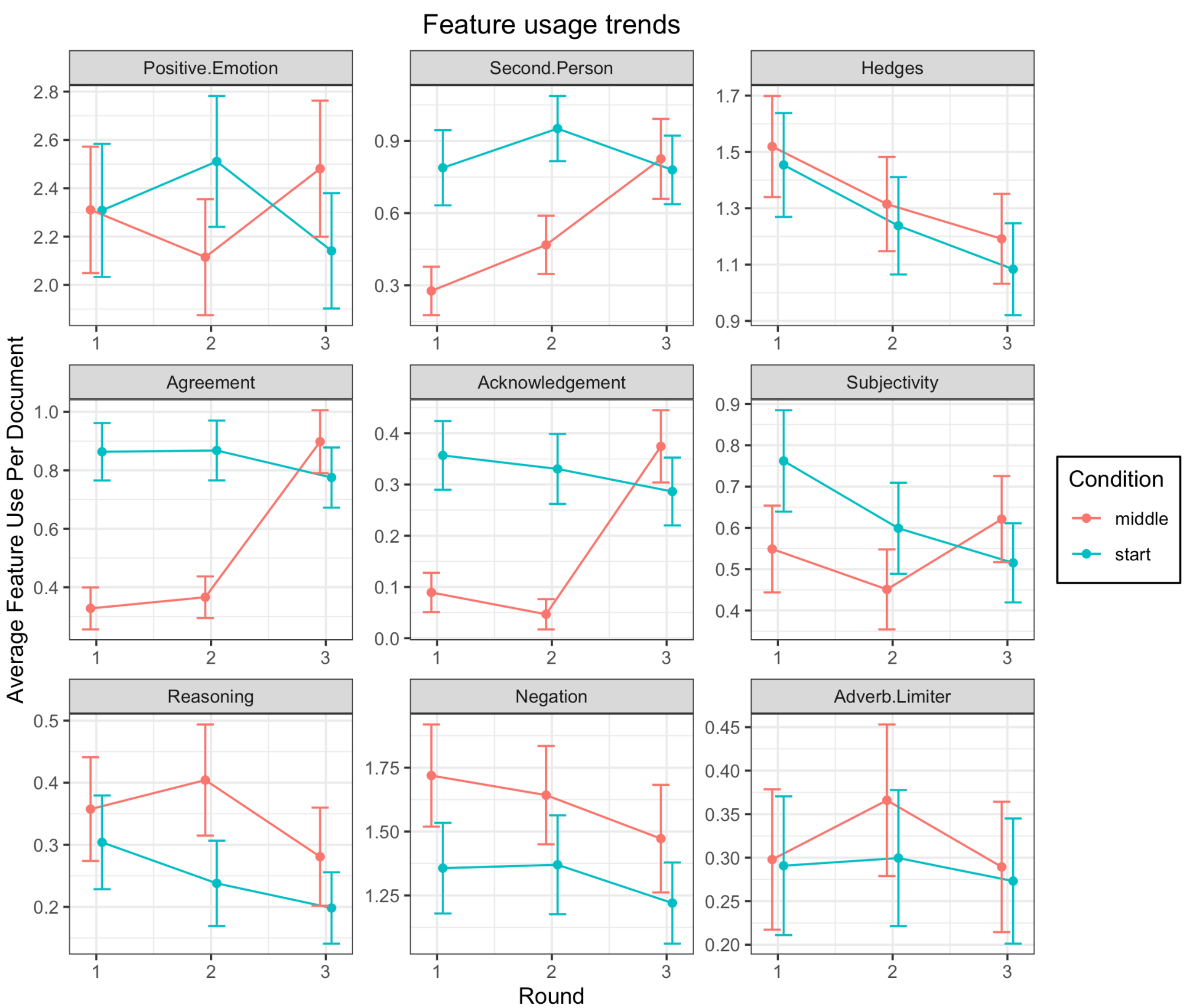


Figure 5. Flow chart depicting the protocol steps participants go through after they have completed the attention checks in Qualtrics. Participants were initially shown the receptiveness recipe before round 1 and were then randomly assigned to either the generic condition or the feedback condition. After each round, participants were shown either the receptiveness recipe if they were assigned the generic condition, and the feedback message if assigned the feedback condition. After the 4th round, participants were asked a series of questions on technology adoption, subjective learning, relationship improvements, willingness to engage and finally, questions demographics.

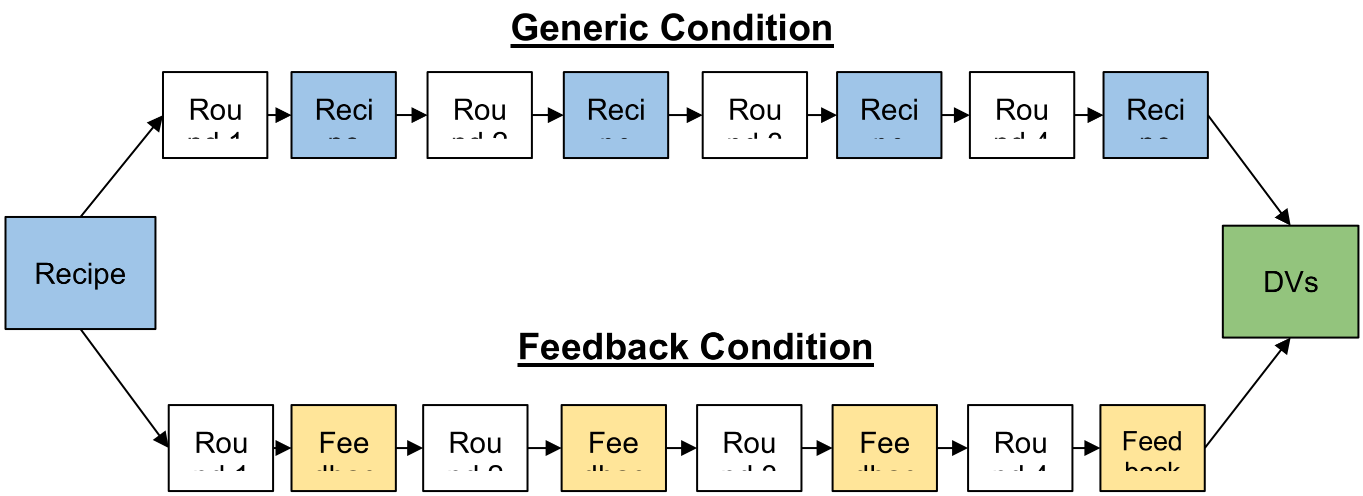


Figure 6. Comparing average receptiveness scores by round and by condition for study 2. Each data point represents a group mean as a percentile and their corresponding 95% confidence interval.

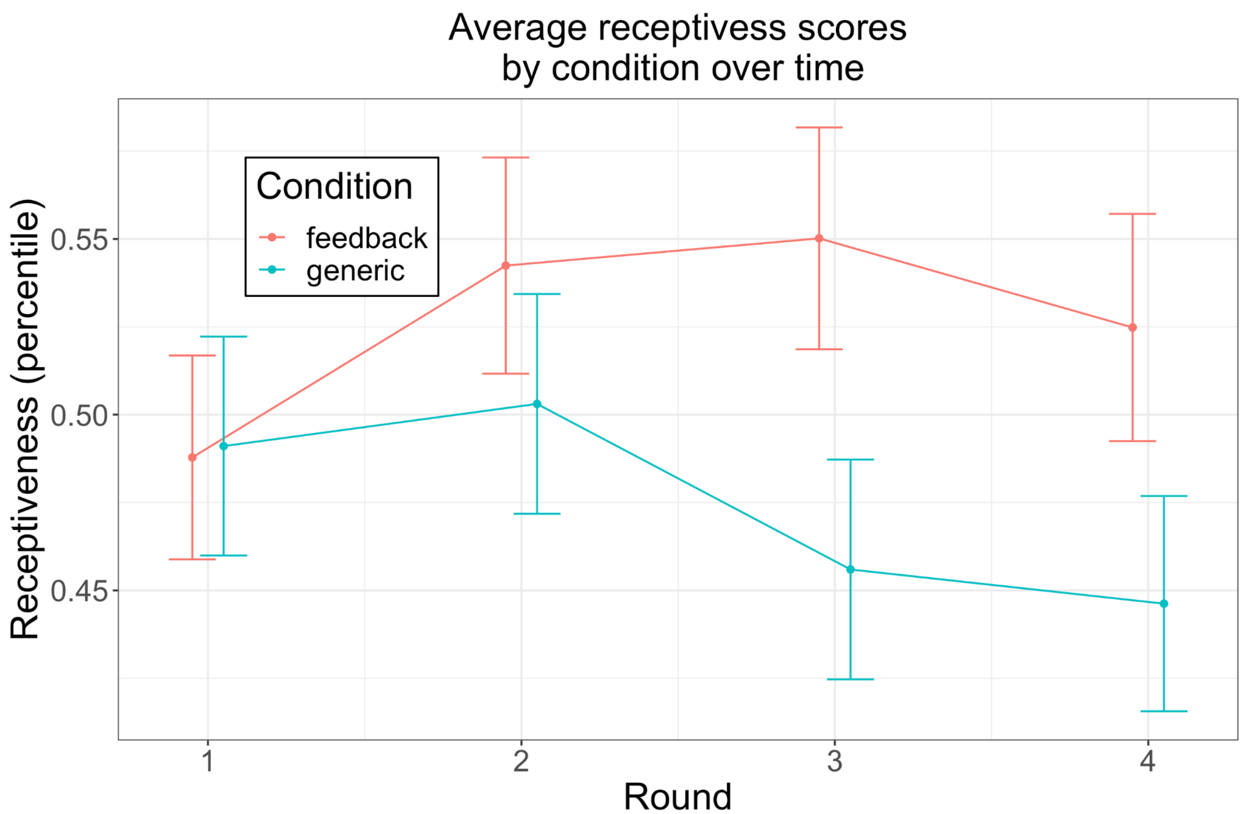


Figure 7. Comparing average feature usage per document for each of the key linguistic features by condition. The data was aggregated for rounds 2 to 4 after participants have had an opportunity to be shown the receptiveness recipe and the feedback message. Each data point shows the average feature count per document and their corresponding 95% confidence intervals.

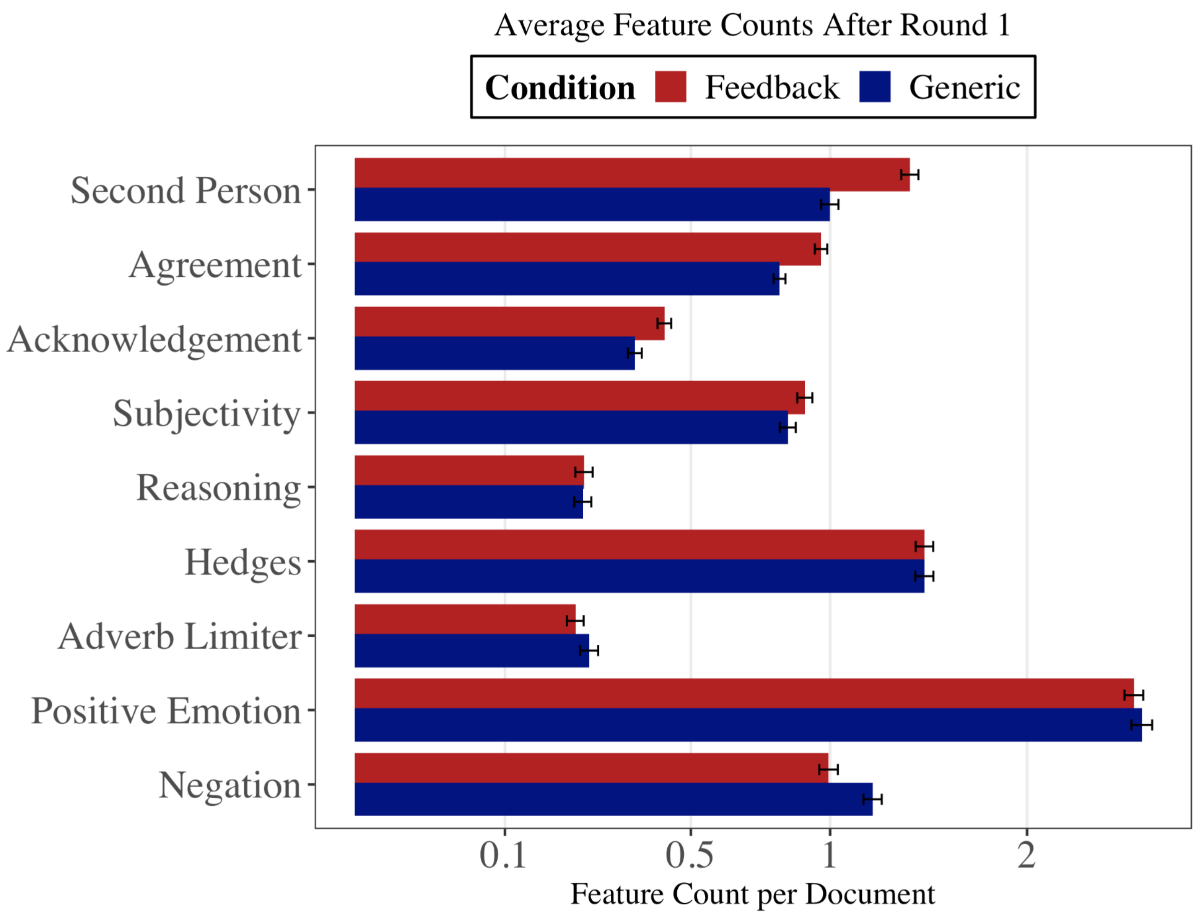


Figure 8. Comparing feature usage trends over time by key feature and condition. Each data point represents the average feature use per document and their corresponding 95% confidence interval.

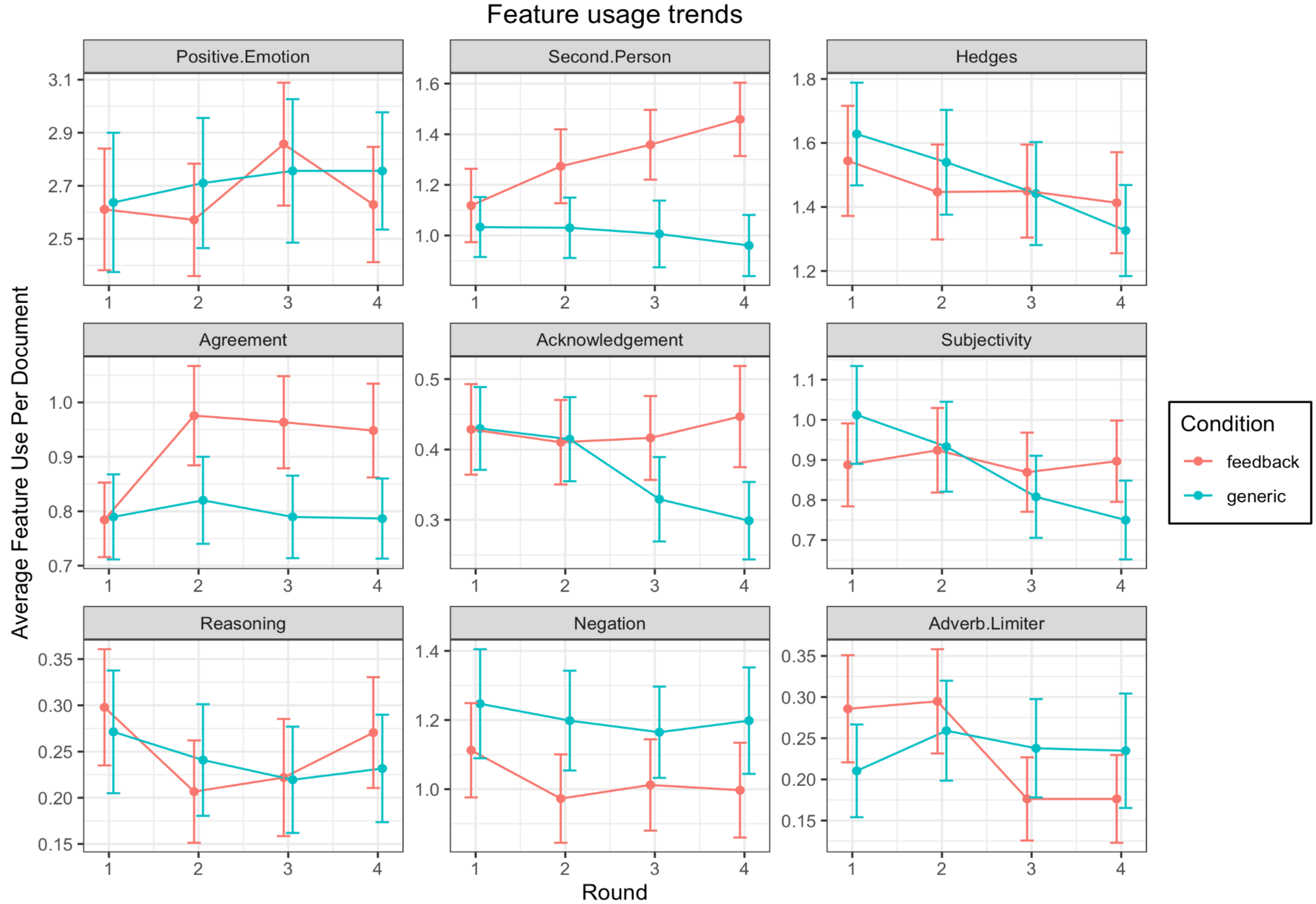
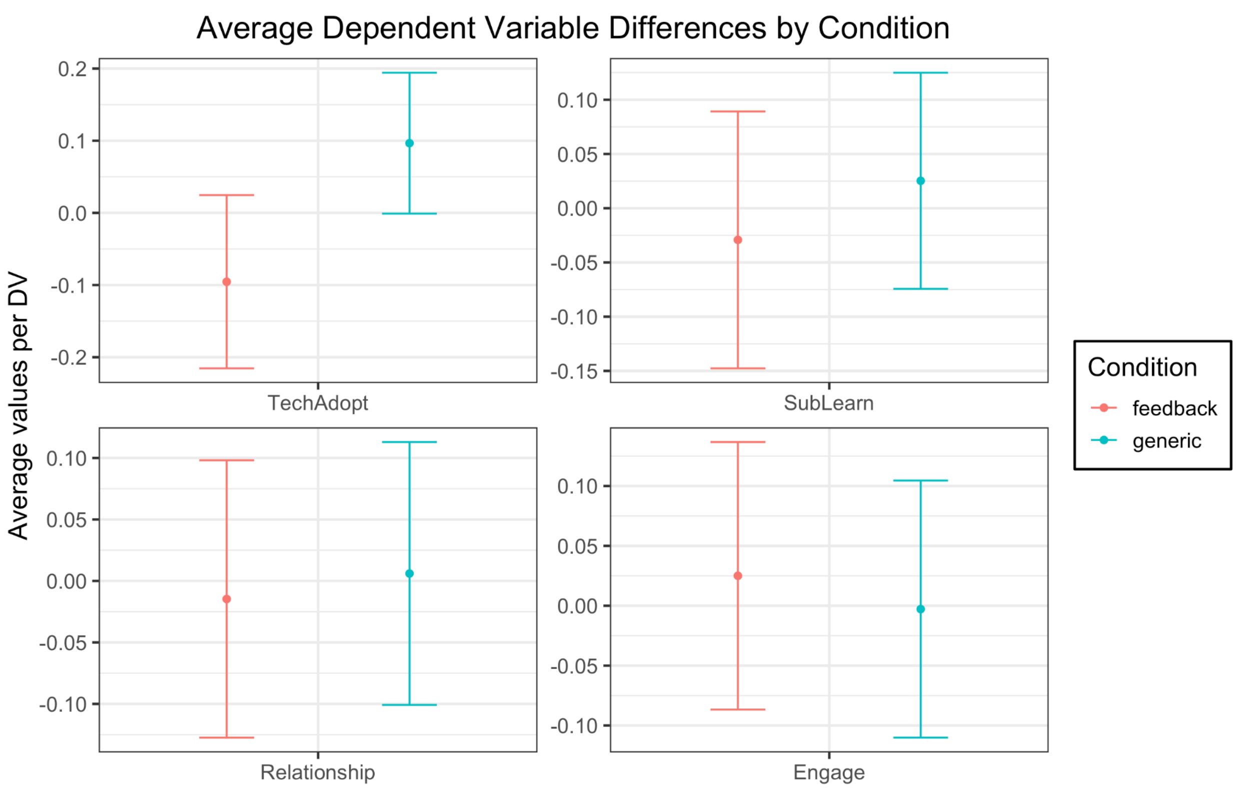


Figure 9. Comparing means of the dependent variables (excluding Receptiveness). Each data point shows the mean values as answered by participants on a Likert scale from 1-7 along with their respective 95% confidence intervals.



Appendix A. Qualtrics survey questions from all studies.

Study 1

Adoption difficulty. Participants are asked to “Now we'd like you to think about some people you talk with in your own life who hold opposing views. You could disagree with them about any issue that's important to you (life, work, politics, etc.).

Consider the communication style you used to write your last response in this survey. How hard would it be for you to adopt a similar style in future interactions with the disagreeing others in your life?” on a scale of 1: Not at all to 7: Extremely.

Likelihood of adoption. Participants are asked to “Again, consider the communication style you used to write your last response in this survey. The next time you interact with the disagreeing others in your life, how likely are you to adopt a similar style?” on a scale of 1: Not at all to 7: Extremely.

Trust. Participants are asked to “Imagine we showed your last response to the person who wrote the statement to which you responded. What do you think that person would say about you, based on your response? It may be difficult to make these ratings imagining you are someone else, but just do your best!

Please respond to indicate what you think the other person will think about you after reading your response Remember, this person will only see your most recent response, as well the statement they originally wrote.” on a scale of 1: Not at all to 7: Extremely.

1. How much do you think the statement writer would like to have you on a work team?
2. How much would you think the statement writer would like having you to represent them in a professional context?
3. How much do you think the statement writer would trust your judgment to make good decisions in complex situations?

Study 2

Relationship improvement scale. Adapted from (Abbas et al., 2014, Tynan, 2005, Yeomans et al., 2020). Participants are asked to “Consider the things you learned about receptiveness strategies in this study. How might this affect your relationship with someone when discussing a topic the two of you strongly disagree with? Please rate how much you agree with the following statements.” on a scale of 1: Not at all to 7: Extremely.

1. I feel I am better able to express my opinions while maintaining a healthy relationship.

2. I am less concerned about the potential damage to my relationship when I express my opinions.
3. If I am having a difficult discussion, I will be better able to prevent escalation of conflict.
4. I feel that I will gain more respect when I express my opinions.

Technology adoption. Participants are asked to "Consider a future conversation you will have with someone you respect (at home, at work, in your neighborhood, etc.), about a topic on which the two of you strongly disagree. This would be a situation where you might potentially use the receptiveness strategies you just learned about in this study. Answer the following questions." on a scale from 1: Not at all to 7: Extremely

1. How likely are you to use the receptiveness strategies you learned about in future personal conflict?
2. How difficult would it be for you to use the receptiveness strategies you learned about in this future personal conflict?
3. How much would you want to practice with the materials from this study before your next personal conflict?
4. How much will you try to use the strategies you learned today in this future personal conflict?

Subjective Learning. Participants are asked to "Consider what you knew about writing a receptive statement prior to this study and what you learned during the study. Please answer the following questions." on a scale from 1: Not at all to 7: Extremely

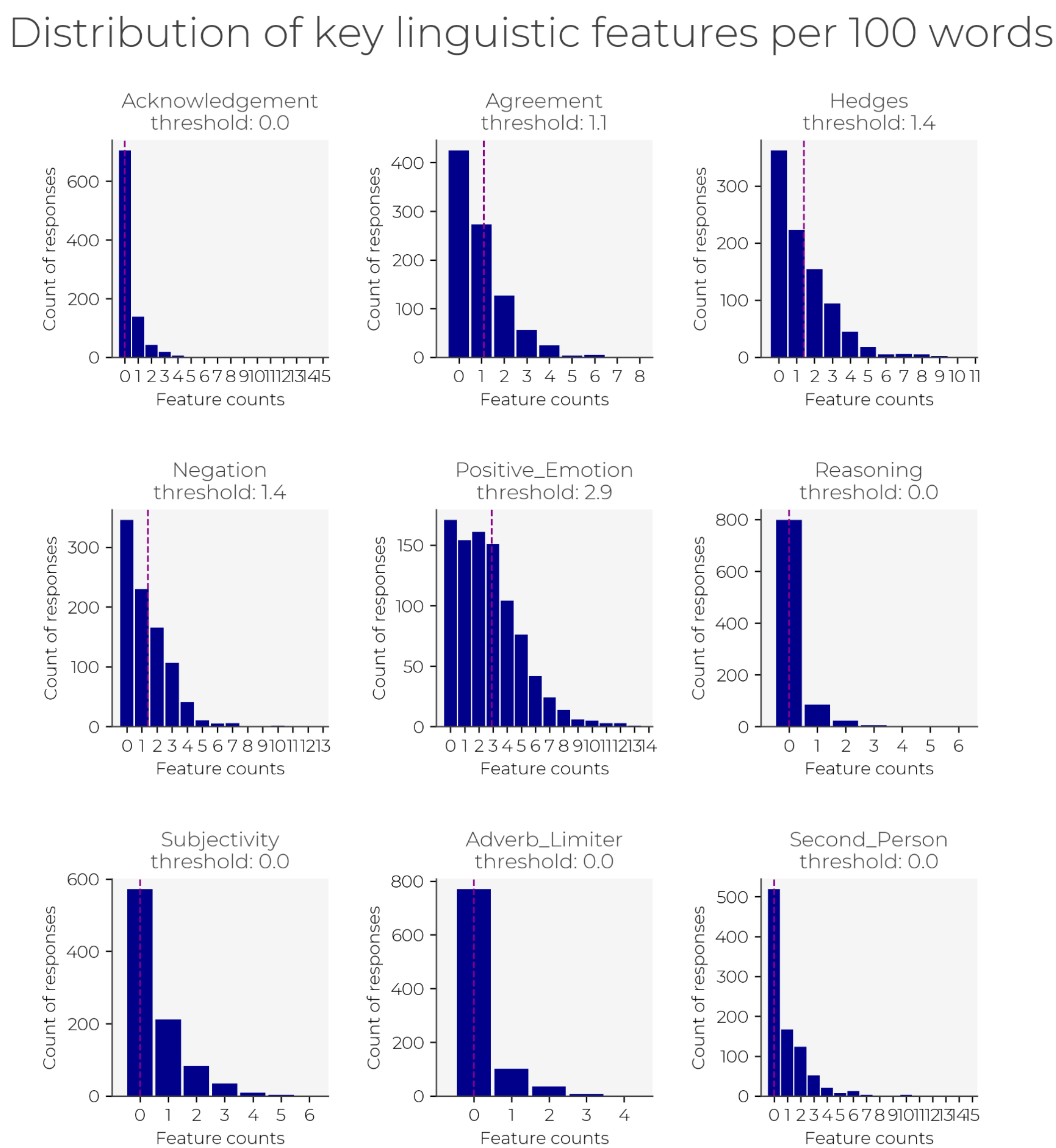
1. Will the things you learned about receptiveness help you in your future personal conflicts?
2. Do you think you learned how to be more receptive from this study?
3. Did the things you learned about receptiveness fit into your own approach to conflict?
4. Did the information in the study help you learn how to be more receptive in conflict?

Willingness to Engage. Additional questions designed to gauge potential longer-term impact. Participants are asked to "Consider the things you learned about conflict management during this study and how it may change your approach to difficult conversations. Please rate how much you agree with the following statements." on a scale from 1: Not at all to 7: Extremely.

1. I am likely to respond to another person who has a strong opposite view to myself.
2. I am more likely to avoid responding to another person who has a strong opposite view to myself.

Appendix B. Plots describing thresholds from feedback system

The thresholds were generated from the dataset of receptiveness responses from a previous study (Yeomans et. al., 2020). Any responses written by participants who had not received the “receptiveness recipe” were excluded from this threshold analysis. These exclusion criteria left us with a sample size of 916 from 1386 responses in total. For each of the 916 responses, we applied the feedback algorithm to count the number of features. From these counts, we plotted a histogram for the 9 key features. The threshold was equal to the mean of the feature distribution. See charts below for visualization. Feature counts were normalised per 100 words. We expect longer statements to contain more of certain features than others which may result in a bias in the thresholds.



Appendix C. Feedback statements

Feedback statements for features expecting to have a positive effect on receptiveness:

Feature	**Above Threshold**	**Below Threshold**
Agreement	The algorithm noticed you **used enough** agreement phrases (e.g. "I agree", "you are right"). **Keep using these phrases**!	The algorithm noticed you **could use more** agreement phrases (e.g. "I agree", "you are right"). **Use more of these phrases** next time! They will make you seem **more** receptive.
Positive Emotion	The algorithm noticed you **used enough** positive emotion words (e.g. "adore", "happy"). **Keep using these words**!	The algorithm noticed you **could use more** positive emotion words (e.g. "adore", "happy"). **Use more of these words** next time! They will make you seem **more** receptive.
Subjectivity	The algorithm noticed you **used enough** subjective phrases (e.g. "I believe" or "In my opinion"). **Keep using these phrases**!	The algorithm noticed you **could use more** subjective phrases (e.g. "I believe" or "In my opinion"). **Use more of these phrases** next time! They will make you seem **more** receptive.
Acknowledgement	The algorithm noticed you **used enough** acknowledgement phrases (e.g. "I understand" or "I get"). **Keep using these phrases**!	The algorithm noticed you **could use more** acknowledgement phrases (e.g. "I understand" or "I get"). **Use more of these phrases** next time! They will make you seem **more** receptive.
Hedges	The algorithm noticed you **used enough** hedging words (e.g. "sometimes" or "maybe"). **Keep using these words**!	The algorithm noticed you **could use more** hedging words (e.g. "sometimes" or "maybe"). **Use more of these phrases** next time! They will make you seem **more** receptive.
Second Person	The algorithm noticed you **used enough** second person phrases (e.g. "you" or "yourself"). **Keep using these phrases**!	The algorithm noticed you **could use more** second person phrases (e.g. "you" or "yourself"). **Use more of these phrases** next

		time! They will make you seem **more** receptive.

Feedback statements for features expecting to have a negative effect on receptiveness:

Feature	**Above Threshold**	**Below Threshold**
Reasoning	The algorithm noticed you used **too many** reasoning phrases (e.g. “therefore”, “because”). Try to **decrease this** next time! They will make you seem **less** receptive.	The algorithm noticed you **avoided** reasoning phrases (e.g. “therefore”, “because”). Keep **avoiding** these phrases!
Negation	The algorithm noticed you used **too many** negation words (e.g. “did not”, “would not”). Try to **decrease this** next time! They will make you seem **less** receptive.	The algorithm noticed you **avoided** negation words (e.g. “did not”, “would not”). Keep **avoiding** these phrases!
Adverb Limiter	The algorithm noticed you used **too many** adverb limiters (e.g. “just”, “only”). Try to **decrease this** next time! They will make you seem **less** receptive.	The algorithm noticed you **avoided** adverb limiters (e.g. “just”, “only”). Keep **avoiding** these phrases!