Influencing laughter with AI-mediated communication

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Abstract

Previous experimental findings support the hypothesis that laughter and positive emotions are contagious in face-to-face and mediated communication. To test this hypothesis, we describe four experiments in which participants communicate via a chat tool that artificially adds or removes laughter (e.g. *haha* or *lol*), without participants being aware of the manipulation. We found no evidence to support the contagion hypothesis. However, artificially exposing participants to more *lol*s decreased participants' use of *haha*s but led to more involvement and improved task-performance. Similarly, artificially exposing participants to more *haha*s decreased use of *haha* but increased lexical alignment. We conclude that, even though the interventions have effects on coordination, they are incompatible with contagion as a primary explanatory mechanism. Instead, these results point to an interpretation that involves a more sophisticated view of dialogue mechanisms along the lines of Conversational Analysis and similar frameworks and we suggest directions for future research.

1. Introduction

One of the most pressing questions in communication research is how social media platforms affect communication. Are platforms amplifying and spreading outrage, hatred, and anger, trapping users in filter bubbles of negative emotions? Could platforms be redesigned to attenuate the spread of negativity? In order to understand how emotions spread online we need to know the underlying mechanisms of how people influence each other's emotions, and how these mechanisms are transformed by social media platforms. Historically, mediated communication, especially text-based instant messaging, has often been characterised as an impoverished medium, as it doesn't transmit smiles, frowns, head nods, laughs, sighs, gestures, as well as a panoply of other non-verbal behaviours. But this is not the case. Users adapt to the medium, creatively developing novel cues, e.g., emoticons :) , written laughter (e.g., "haha", "lol"), punctuation ("Yes!!!!!") or novel spelling, e.g., lengthening ("Nooooooooo" or "hahahahah", "lololol"). However, it is still unclear how these cues might influence users' emotions (Liebman and Gergle, 2006).

More recently, the role of social media algorithms in spreading emotions has become a core issue: Unlike historic forms of mediated communication such as the telephone, letter, or radio, communication via social media is mediated by ever-increasingly sophisticated A.I. algorithms (Hancock, Naaman and Levy, 2020; Hohenstein and Jung, 2020), which suggest to users what messages to send, which messages the recipient sees, the order in which messages are displayed, and also determines how long messages are displayed. Social media algorithms learn from users' interactions which cues (i.e., which words, phrases, punctuation, emoticons, emoji, etc.) increase user engagement, and subsequently promote these messages. It is claimed that since messages containing negative emotions are more readily shared (Rozin and Royzman, 2001; Bebbington et al., 2017; Acerbi, 2019), social media algorithms promote these messages, consequently amplifying negative emotions across the platform (De Vito, Gergle et al., 2017). However, investigating these claims is difficult. Social algorithms operate as black boxes whose workings are closely guarded commercial secrets while it is also widely admitted that not even the designers of such algorithms completely understand how they work (see e.g., Castelvecchi, 2016; Adadi and Berrada, 2018; Arrieta et al., 2020). Users are often unaware which messages have been promoted, demoted, or hidden from view (Rader and Gray, 2015; Eslami et al., 2015). The workings of the black box are similarly opaque to researchers. Without having privileged access to the inputs, processing, and outputs of the black box it is impossible to determine whether AI-mediated communication can in fact influence users' emotions, and if so, which cues in users' messages might the algorithms be identifying in order to promote, demote, or hide users' messages.

In order to address these questions this paper describes a set of experiments which investigate the putative role of laughter in spreading positive emotion and positively influencing collaborative performance, using AI-mediated communication as an experimental technique.

The paper proceeds as follows. First, we describe psychological theories that propose that emotions are spread via mimicry of behaviour, as well as conversation analytic accounts of how laughter is deployed in interaction. Then we describe experimental research and observational studies on mimicry, emotional transmission, and laughter in instant messaging. We report results from four experiments which use an experimental instant messaging platform to manipulate users' conversations in real-time in order to examine the role of laughter in spreading positive emotion. We conclude with discussion of the implications of our research for the study of influencing emotion transmission in computer-mediated communication.

2. Laughter and emotional contagion

According to an enduring folk-psychological belief, expressions of emotion, especially laughter, are contagious. A wide range of research seems to support this view. For example, Young and Frye (1966) found that participants who listen alone to jokes laugh less than participants who listen together in groups, even though participants in both conditions rate the jokes as equally funny. Similarly, higher amounts of laughing can be induced in an audience by playing canned laughter, by showing other people laughing (Provine, 1992; Bush, Barr, McHugo, & Lanzetta, 1989), or by increasing the group-size (Butcher and Whissell, 1984). Contagiousness of laughter is explained by the assumption of unconscious behavioural mimicry, namely, that an individual, without overt intention or awareness, imitates the behaviour of their interactional partner (Chartrand & Bargh, 1999; Chartrand & Jefferis, 2003; Chartrand, Maddux, & Lakin, 2005, Bargh & Chartrand, 2014). Mimicry has been attributed to a direct link between perceiving a behaviour and performing that same behaviour (Chartrand & Bargh, 1999; Dijksterhuis & Bargh, 2001, cf. Heyes, 2011).

Beyond mimicking of behaviour, it has also been argued that mimicry facilitates the sharing of presumed internal states such as beliefs, emotions, and moods. Emotions and moods are supposed to be "infectious" (Hatfield et al., 1994). According to the theory of "emotional contagion", people can "catch" emotions from each other as a result of largely automatic processes like priming. When people interact with each other, they produce verbal and non-verbal behaviours that are associated with their emotional state (e.g., smiles, gestures, body posture). Their interlocutors tend to mimic these behaviours tacitly and automatically, and, consequently, feel a "weak reflection" (Hatfield, Carpenter, Rapson, 2014) of their conversational partner's emotions. A large body of work has focused primarily on the variety of non-verbal cues that purportedly underpin transmission of emotions, e.g., via mimicry of facial expressions (Adelmann & Zajonc, 1989; Matsumoto, 1987), vocal mimicry (Cappella and Planalp, 1981; Chapple, 1982) and postural mimicry (Bernieri, Davis, Knee, & Rosenthal, 1991).

In this connection, posture matching has been seen as a potential non-verbal indicator of group rapport (Scheflen, 1964). On the other hand, Bavelas et al., (1986) argue that mimicry is a tool used to communicate liking for and rapport with another. Subsequent research also demonstrates that posture sharing is indicative of involvement and interest in an interaction, and feelings of togetherness. In a typical study, students were asked to report the level of rapport in their classes, and those classes were then coded for amount of posture sharing. As predicted, classes rated by students as having high rapport also manifested the greatest amount of posture sharing (La France & Broadbent, 1976).

Similarly, in conversational interaction, it has been argued that people mimic their partner's phonological, lexical, and syntactic patterns, as well as their non-verbal behaviour. According to the Interactive-Alignment model (Pickering and Garrod, 2004), common ground in conversation is established via mimicry: priming mechanisms operate at multiple levels of representation that result in automatic alignment of the dialogue participants' situation models (but cf. Healey et al., 2014; Mills, 2014; Fusaroli and Tylen, 2016; Fischer, 2016; Strupka et al., 2016).

Mimicry and contagion theories have gained support from neuroscientific advances around the discovery of "mirror neurons" (Rizzolatti, 2004, 2005; Rizzolatti et al., 1999), which fire both when primates perform an action and also when they observe another primate performing the same kind of action. Strong proponents of this view suggest that these neural mechanisms of mirroring behavioural cues underpin intersubjectivity – including mindreading, emotional contagion, and underpin empathy and prosocial behaviour in humans and other primates (Blakemore and Frith, 2005; Hatfield, Carpenter, Rapson, 2014; Barsade, 2002). The hypothesis is that when we observe someone displaying a behaviour, e.g., laughing, this activates the same brain region that is associated with our own laughter response – explaining the contagiousness of laughter and, potentially, the emotional contagion of happiness and rapport associated with that laughter. For example, it is argued that increased premotor cortex activation associated with listening to sounds of laughter is linked to managing negative emotions (e.g., fear, anger, disgust) by reducing stressful reactions characteristic of unpleasant emotions and, as a result, promoting social cohesion and rapport. Warren et al (2006) argue that people are primed to laugh by passively listening to laughter irrespective of whether there is sharing of the emotional experience triggering the laughter and that such mirroring can have strong positive effects in human interaction. Thus, it is assumed that laughter perception from another individual will activate the motor system associated with producing own facial expressions, e.g., smiles, which enables emotional understanding and empathy and underpins central affiliative aspects of human communication like coordination in conversation and contagious laughter (McGettigan et al., 2015; Scott et al. 2014; Scott, Sauter & McGettigan, 2010).

Laughter in face-to-face interaction

Laughter is a universal human behaviour that occurs primarily in a social context (Provine and Fischer, 1989). It is now widely acknowledged that, rather than being an individualistic expression of emotion, laughter in face-to-face (f-t-f) interaction is instrumental in building up and sustaining social connections (Bryant, 2020; Bryant et al., 2020). Thus, f-t-f social laughter is taken to be a central case of "contagion" (Provine, 1992) or a "resonance behaviour" (Rizzolatti et al., 1999). It is also assumed that laughter elicits positive emotions in the partner with "antiphonal laughter", i.e., instances of reciprocated laughter that occur during or immediately after a social partner's laugh (Smoski and Bachorowski, 2003), indicating cooperative and affiliative intentions (e.g., Dunbar, 2012; Davila-Ross et al, 2011; Flamson & Bryant, 2013; Owren & Bachorowski, 2001), increasing within-group cooperation and cohesiveness (Banning and Nelson, 1987; Vinton, 1989; Greatbatch and Clark, 2003). In contrast, when a partner's laugh is not reciprocated, it may be an indicator that something is wrong with the interaction, for example, a misunderstanding, status, or power negotiation, or, even, disaffiliative emotions like mocking, teasing, schadenfreude (e.g., Buckley, 2014; Eibl-Eibesfeldt, 1970).

Interactive negotiation of laughter

Psychological and neuroscientific investigations have focused on f-t-f laughter as the expression of supposed internal private emotional states (Ruch & Ekman, 2001; Martin, 2010). Yet, from a conversation analytic (CA, Schegloff, 2007) view, the "contagion" account stems from a rather naïve treatment of laughter which ignores its rich, highly contextualised function. Under this view, interlocutors do not simply perceive laughter as an instinctive, uncontrolled reaction to some stimulus. Instead, laughter is an interactive resource, a joint affordance. While it is true that laughter can sometimes invite laughter (Jefferson, 1979), even in such cases, it is not true that the elicited laughter always has the same function as the original cue. First, it is usual that laughter might not be reciprocated (e.g., Haakana, 2002). For example, laughter in "troubles-tellings" is not an invitation to shared laughter (Jefferson, 1984). Moreover, although the invited laugh is typically produced immediately after some initial laughter, the invited laugh can also be postponed – e.g., after the initial invitation to laugh, the second speaker may produce a "side sequence" (Jefferson, 1972), typically an intervening turn, before initiating laughter. Glenn (2003) argues that such side sequences, where the responsive laughter is produced at a particular juncture, shows that laughter is not an "instinctive reaction to a stimulus", but is instead "organised, systematic, and finely coordinated with features of surrounding talk" (Glenn, 2003: 61).

The simple observation from CA studies then is that laughter is not a direct conditioned response to something funny, but, instead, is used to accomplish a wide variety of actions, such as treating the current talk as non-serious (Holt, 2013), topic-management (Holt, 2010), dealing with interactional "trouble" (Holt, 2012), turn-taking (Ikeda and Bysouth, 2013), and to display embarrassment (Glenn, 2013) as well as many other uses (Petitjean and Morel, 2017). Consequently, Glenn (2003) distinguishes between four different types of laughter in conversation: laughter which invites laughter by the other, invited laughter, uninvited (or "volunteered" laughter), and laughter which does not invite laughter by the other.

Given these complex communicative and intentional functions of laughter and other non-verbal behaviours which interact with verbal phenomena, some linguists argue that laughter, like verbal/written language, conveys its own propositional content that interacts with verbally conveyed propositional content (Plessner, 1970; Ginzburg et al., 2015, 2020; Tian et al., 2016; Eshghi et al., 2019). In these theories, far from being an automatic response of emotional contagion, the interpretation of laughter by the audience involves highly complex reasoning processes requiring contextual inferences about attentional, emotional, and intentional internal states (Reddy, Williams, & Vaughan, 2002; Ginzburg et al., 2015, 2020; Mazzocconi, 2019). This is because the propositional content of laughter and the speech act it performs are highly underspecified and context-dependent. In that, laughter particles are very similar to indexicals, pronouns or response particles like *yes* or *no*. Accordingly, Ginzburg et al., (2015, 2020) propose lexical entries for laughter tokens that include a semantics: the core meaning of laughter involves a predication *P*(*l*), where *P* is a predicate and *l* is an anaphoric element standing for the 'laughable' (the event that merits laughing about). The antecedent of this anaphoric element will be an event or state referred to by a dialogue utterance or in need of retrieval from the context. *P* is an ambiguous predicate characterising the laughable as either 'Incongruous' relative to the context or as 'Pleasant' for the laughter initiator, the laugher. From this basic ambiguity that must be resolved for the utterance to be processed successfully, various interpretational effects can be further achieved as the result of contextual inference resulting in additional meanings like irony, mockery, doubt, but also agreement and affiliation. In terms of placement, in contrast to Provine (1993), who assumed that laughter is related to the immediately preceding utterance, here free alignment between laughter and its antecedent laughable is assumed, which, therefore, imposes more complex inferencing to resolve the laughter's antecedent, i.e., the laughable, as the latter cannot be derived simply by examining the sequential context (Mazzocconi, 2019: 194).

In contrast, work in CA and other action-oriented frameworks assumes that laughter lacks any semantic propositional content (Glenn, 2003). From this perspective, verbal and non-verbal signals are taken as offers for joint conversational actions ('affordances', see, e.g., Gregoromichelaki et al., 2020; Ham, this volume), whose import needs to be negotiated and ratified by the other participants if it is to have an effect in the interaction. This is based on the observation that not even the form of of non-verbal behaviours like laughter, namely, its identification as a laugh particle, can be assumed to be identifiable unambiguously and directly so that it maps to a lexical entry. Instead, the occurrence and communicative function of laughter needs to be negotiated and jointly determined by the participants. "Laughter" from this perspective is a folk psychological notion, and it is recommended that researchers exercise caution with its deployment in analyses. For example, sounds that could be characterised as laughter, e.g., a breath, part of a word, or an exclamation ("equivocal laughs", Glenn 2003) can be specified retroactively as clear laugh particles through participant negotiation (Jefferson, 1979). Thus, the occurrence and meaning of laughter is jointly construable (Clark, 1996) by the interlocutors.

Emotional contagion in text-based mediated chat

An important testbed for theories of emotional contagion is in text-based, computer-mediated communication. This is because, historically, mediated interaction has been characterised as an impoverished medium, which filters out many non-verbal cues, so that any emotional contagion factors can be more clearly identified. In contrast, Social Information Processing theory proposes that people adapt their use and interpretation of communicative cues to the medium, using paralinguistic cues (e.g., word choice, spelling, punctuation, emojis, emoticons and timing) in place of non-verbal cues to overcome CMC limitations of lack of social presence (Walther, 2007; 2016).

In a pair of experiments, Hancock and co-workers tested whether emotional contagion occurs by first inducing negative emotions in participants and then testing whether these negative emotions are transmitted when they subsequently converse via text-based computer-mediated communication (CMC) with a fresh partner. In both experiments, contagion occurred rapidly – after about 15 minutes, the fresh partners assessed themselves as being more negative (Hancock et al, 2008), affecting performance in a collaborative task. However, the exact reasons as to why these outcomes can be characterised as "contagion" are unclear: First, the transmission of emotions was not entirely "faithful" as the negatively induced participants reported feeling frustrated and annoyed, while their partners reported feeling more tension and alarm (Guillory et al., 2011). Second, it is also unclear how aware of the emotional states of their partners participants are, since some participants did not detect the negative emotions of their partner, while others did. Third, and most importantly, it is unclear exactly which cues might be driving this process: Hancock et al. (2008) found that negatively induced participants produced more sad words, which potentially primed the fresh participant, whereas Guillory et al, (2011) observed negative emotions spreading to the partner without any observable change in frequency of emotion-related words. A subsequent experiment (Kramer et al, 2014), also provides evidence of contagion that might not arise via mimicry of words. This study experimentally manipulated Facebook users' News Feeds so that users either saw fewer positive updates or fewer negative updates from their Facebook friends. The results showed that participants who saw fewer positive updates subsequently produced updates with fewer positive emotions and more negative emotions. Similarly, users who saw fewer negative updates produced updates with fewer negative emotions and more positive emotions. The authors argue that this form of contagion cannot arise simply via mimicry of emotion words, since the effect of negative emotions on positive emotions (and vice versa) cannot arise by straightforward copying. However, since the experimental manipulation blocks entire messages, the experiment cannot determine which particular constituent elements of the messages, such as emojis, punctuation, laugh particles, misspellings etc., might be responsible for this outcome.

This question is addressed by Liebman & Gergle (2016) in a related study that examines how interactional use of paralinguistic cues affects the interpersonal, relational outcomes of the interaction. In this study, pairs of participants discussed a moral dilemma, via text-based chat in which participants' turns were artificially transformed so that specific cues were removed (emoticons, exclamation marks, interrobangs, asterisks for *emphasis* and words all in capital letters, e.g., SO GREAT). Crucially, the participants whose cues were removed were not aware that they had been removed. The experimenters found that the number of cues used by a partner is positively correlated with the number of cues used by their partner – but this effect vanished for participants whose cues were removed by the server – suggesting that participants are entraining to or mimicking each other's cues (cf. Pickering and Garrod, 2004). In other words, the cues themselves are "contagious". The experimenters also found that participants' cues influence participants' perceptions of affinity, an effect which also vanishes when the cues are removed from the participants' turns. The researchers suggest that the perception of reciprocity of cue use influences participants' affinity towards each other.

So, in summary, this literature indicates that in text-based interaction, people demonstrably affect each other's emotional states, without being aware of it, potentially giving rise to a feeling of affinity and prosocial behaviour. This effect is necessarily driven by textual features in the interaction, and experimental work suggests that choice of words, spelling, and paralinguistic cues such as emoticons, emojis, lengthenings, as well as "chronemic" cues[1] contribute towards contagion. Yet so far, despite laughter in f-t-f conversation being identified as one of the main mechanisms of transmission of emotional states, no similar study has been conducted in online interaction to test whether forms of written laughter, such as *haha*, *hehe*, or *lol* (i.e. *"laugh out loud"*) might play a role in emotional contagion online. Further, the experiment by Liebman and Gergle (2016) raises the intriguing possibility that written laughter (like laughter in f-t-f interaction) might also be contagious.

Laughter in text-mediated communication

Besides acoustic properties, laughter in f-t-f communication also has iconic visual properties such as

doubling over, body shaking, rapid breathing, and movement of the eyes. However, since text-mediated communication does not convey acoustic or bodily cues, people have adapted the available textual means to such purposes. Textual representations of laughter can be expressed through either the inclusion of onomatopoeic expressions (*haha*), acronyms (*lol*, laugh-out-loud), or emoticons (:)) and emojis (☺) (Christopherson, 2013; Kadir et al., 2012). McKay (2015) uses the term "written laughter", Varnhagen et al. (2010) use the term "emotion words", and König (2019) uses "laugh particles" for expressions like *haha* and its variants.

[1] These are cues that relate to the time of transmission of the message, for example, the time of day the message was sent or how long it took for a participant to answer (see, e.g., Kalman et al., 2013).

It is currently unclear how much the communicative function of written laugh parallels that of f-t-f laughter, in large part due to the quasi-asynchrony of instant messaging placing different constraints on turn-taking (Herring, 1999). In instant messaging, if a participant laughs inviting the other to laugh, the recipient only receives the invitation when receiving the whole turn. Similarly, the sender of the invitation to laugh only has evidence that the recipient has taken up the invitation to laugh after receiving the full turn containing the laughter. Thus, in contrast to f-t-f interaction, where, as soon as a speaker invites the other to laugh, the recipient of the invitation can immediately accept the invitation and start laughing, in instant messaging, this is effectively impossible. McKay (2020) argues that since this disrupted turn-adjacency (Herring, 1999) generally makes it impossible for participants to take up the invitation at the moment it is produced, the offer/acceptance patterns that are found in f-t-f conversational interaction are altered. In text-chat, laughter must be produced sequentially, in separate messages by both participants, and within messages that are separated spatially on the user interface.

A further consequence of this quasi-asynchrony is that, unlike spoken interaction, where laugh particles often have a projective function of announcing an “upcoming laughable” (an event that merits laughter) within a turn, in quasi-asynchronous chat, laugh particles typically only have a responsive function of commenting on things that have already been introduced into the dialogue (König 2019). So, according to McKay (2020), Schneebeli (2020), and Petitjean and Morel (2017), both solo laughter as well as message-initial laughter in mediated interaction are consistently used to respond to a previous turn, treating the previous turn by the other as a “laughable”, while message-final laughter is more likely to be associated with treating the current message as containing the “laughable” (König 2019). Consider Example 1 below:

1	**A:**	this one looks like a strange butterfly
2.a	**B:**	*haha* mine is a like a fat cloud
2.b	**B:**	mine is like a fat cloud *haha*

Example 1: Turn-initial vs. Turn-final laughter

Plausibly 2.a is taken by A to be treating A’s turn as containing a “laughable”, functioning as a second pair-part in an adjacency pair (Schegloff, 2007), whereas 2.b is treating B’s turn as containing the “laughable”, serving as an invitation to laugh for A, functioning as a first pair-part.

Given these differences in the expression of laugh tokens in text-mediated communication, the question is whether analyses of laughter and its emotional effects transfer directly to the written signals exchanged by participants. We have seen some evidence that emotional contagion can be observed in such communicative contexts, but the contribution of laugh particles has not been examined.

3. Research questions

In summary, according to theories of emotional contagion, in text-based interaction, as in f-t-f, people are assumed to subconsciously affect each other's emotional states (see also Hanauska and Leßmöllmann, this volume; cf. Ham, this volume). In particular, the positively valenced emotions of a participant can induce the other participant to become more positive, without either participant being aware of it. This "emotional contagion" is then the cause of observed prosocial behaviour and can be harnessed in contexts in which human or artificial communicators seek to influence their audience. In mediated communication, this effect is necessarily driven by the textual features of the interaction, whether by choice of words, spelling, or by paralinguistic cues such as emoticons, emojis, lengthenings (Brody & Diakopoulos, 2011) and chronemic cues. Yet how these cues drive this process is not well understood – it is not even clear whether these cues might themselves be "contagious". In fact, work on how affinity between participants develops (Liebman and Gergle, 2006) suggests that cues play a direct, causal role on the development of affinity, and that the cues themselves might be contagious. Might this also be the case for emotion cues and for laugh particles?

We present data from four experiments which use AI-mediated communication to address the following research questions:

1. *Is laughter contagious?* Can participants be induced to laugh more by artificially exposing them to more laughter? According to the "contagion" hypothesis, participants

who are exposed to more laughter will automatically mimic this laughter, leading to more laughter overall. Conversely, if laughter is artificially excised from the dialogue, will this cause participants to laugh less?

2. *Are emotions contagious?* Can participants' emotions be affected by artificially exposing them to more laughter? According to the "contagion" hypothesis, exposure to more laughter should prime participants with more positive emotions.

3. *Will more laughter induce more participation and alignment?* Hancock et al., (2008) found that participants who were exposed to negative emotions produced fewer words and exchanged messages slower. This leads to the prediction that participants who are exposed to more laughter should become more involved and, consequently, perform better and produce more text (see also Nguyen and Fussell, 2014, who found that highly involved participants use more words in instant messaging). In addition, since textual alignment is assumed to be associated with higher levels of coordination, will participants who receive artificial laughter align with each other more?

4. *Does placement of laughter within a turn affect interpretation?* In contrast to theories of "contagion", conversation analysis (CA) and action-based or linguistic accounts do not predict that simply increasing the quantity of laugh particles should increase contagion. Instead, the quality and positioning of the messages containing the laugh particles is essential: Laugh particles should only beget more laughter if they are treated by

participants as identifying a "laughable" and serving as an invitation for (joint) laughter. Moreover, according to the CA informed theories of laughter in CMC, the exact placement of artificial laugh particles within a message should have a differential effect. Message-final laughter should be interpreted as inviting the other to laugh, while message-initial laughter should be interpreted as taking up an invitation to laugh.

4. Experiment 1: Inserting artificial *haha*

In this experiment, pairs of participants communicate with each other using the Dialogue Experimental Toolkit (Mills et al., 2013). Participants use a customised instant messaging app on their phones (similar to WhatsApp). This allows experimental stimuli to be sent directly to participants in the instant messaging app (similarly to how users can send and receive images in WhatsApp). Since all participants' messages pass through the chat server, participants' turns can be automatically intercepted and modified experimentally, in real-time.

Methods

Participants

The participants (N= 134) were students who received class credit for participating. The experiments were conducted with a mixture of Dutch-speaking and English-speaking students who followed courses on social media in English. All procedures were in accordance with the 1964 Helsinki declaration and were reviewed by the Faculty's

Committee for the Ethical Evaluation of Research (CETO: 72182987). On signing up for the experiment, participants were randomly paired with another participant from the class, and then each pair was randomly assigned to either the *manipulation* group or to the *control* group. Participants did not know the identity of their partner. The chat software used anonymised usernames (p1, p2, p3) to identify participants in the chat. This yielded 34 dyads in the control group (17 English-speaking and 17 Dutch-speaking) and 33 Dyads in the experimental group (20 English-speaking and 13 Dutch-speaking). The dataset consists of 13729 turns.

The collaborative reference task

Participants played a collaborative task that is a simplified version of canonical joint-reference tasks (Clark and Wilkes-Gibbs, 1986; Horton and Gerring, 2002; Bangerter et al., 2020). On each round, participants are sent a randomly selected image from a set of 12 stimuli. Half of the time both participants are sent the same image. Half of the time each participant is sent a different image. The task of the participants is to determine whether they are both looking at the same image or not. Solving each round, therefore, requires participants to communicate with each other about the image they see on their screens, and compare their descriptions with those of their partner. When participants have come to a decision, either participant can enter "/s" to select "same" or "/d" to select "different". There are four possible outcomes to each round: (1) The images are different, and the participants correctly identify that they are different; (2) The images are different, but the participants incorrectly identify them as the same; (3) The images are the same but the participants incorrectly identify them as different; (4) The images are the same and the participants correctly identify them as the same. On receiving the users' decision, the server informs both participants whether their decision was correct or not, updates their score, and then presents the pair with the next set of stimuli. The stimuli used in the task were a variant of Rorschach (1927) inkblot images, as pre-testing showed that these stimuli elicited spontaneous, playful descriptions of the shapes participants saw in the inkblots.

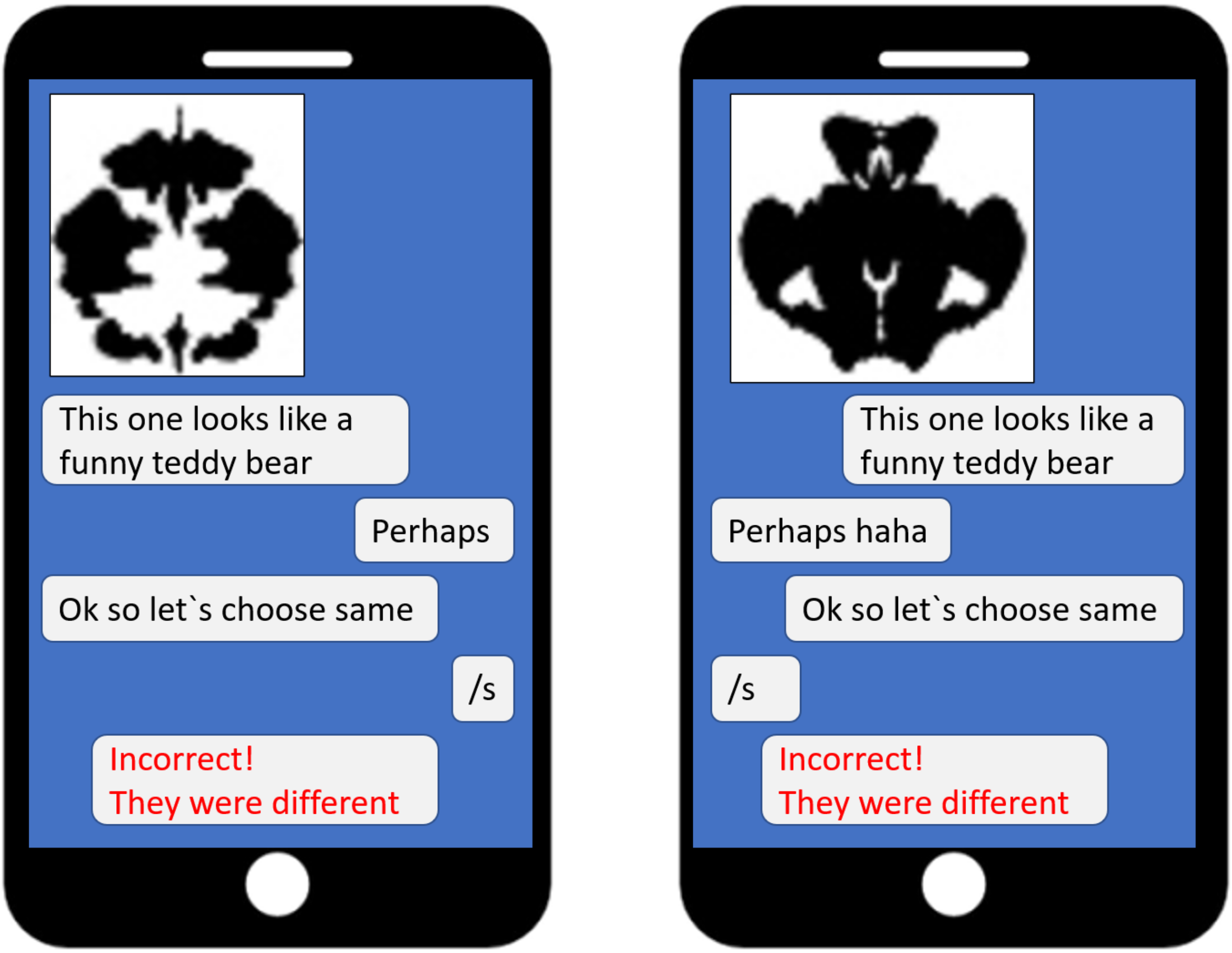

Figure 1 This shows what both participants see on their screens. In this round, both participants are presented with different stimuli, and they incorrectly decide that they

are seeing the same image. Notice also how the turn "perhaps" is artificially modified by the server to "perhaps haha*"*

Experimental manipulation: inserting *haha*

This experiment uses the technique of Transformed Social Interaction (Bailenson, 2006; Cheng et al., 2017; Arias et al., 2018; McVeigh-Schultz, J., & Isbister 2021), which exploits the affordances of mediated interaction in order to experimentally modify participants' communicative behaviour, in real-time, without participants being aware of the manipulation. In the manipulation group, participants' turns were randomly modified by the server to include artificial laughter: Each message produced by a participant was automatically analysed by the server. If the message didn't already contain laughter (e.g., *haha*, *hehe*, *hahaha*), this message has a 1 in 20 chance of being modified by the server. If selected for modification, the server either inserted a laugh particle at the start or at the end of the message. For example, if a participant sent a message such as "this shape looks like a really weird xylophone", the modified message could be "haha this shape looks like a really weird xylophone" or "this shape looks like a really weird xylophone haha". The algorithm also matched the added *haha* with the punctuation of the message, e.g., transforming "This one looks like a clown!" to "This one looks like a clown! Haha". To test whether participants had detected the manipulations, on debriefing, participants were told that the dialogues had been manipulated and were asked to identify the artificial turns. No participants identified the artificial laughter.

Participants in the manipulated condition received on average 21.3 *haha*s (*SD* = 9.5) during the experiment.

Measures:

The data collected from the chat-tool server was used to calculate the following measures:

Laughter

Each turn was automatically classified using regular expressions whether it contained a string that matched *haha* or similar variants, e.g., *hahaha* and *hahhah*.

Happy emojis

Each turn was also automatically classified according to whether it contained an emoji which expresses a positive emotion (i.e. emoji with a smiling face), e.g. 😀😁😂🤣😃😄😅😆😉😎. This category also included “happy” emoticons, e.g., “ :) ”

Sentiment score

To measure the hypothesised effect of the interventions on participants’ emotional state, each message was automatically analysed using the sentiment analysis module of the Pattern toolkit (De Smedt and Daelemans, 2012). This toolkit returns a sentiment score between -1 and +1 which represents the polarity (negativity or positivity of a text).

Task performance

This records how well participants perform in the task, i.e., the proportion of correct trials.

Number of characters

This is a measure of effort, which is calculated by summing the number of characters typed by each participant.

Lexical alignment

This is a measure of the level of linguistic coordination of a dyad. It is calculated by first determining the number of unique words that are used by a dyad, and then calculating the proportion of these words that are used by both participants. A higher value of this score means that both participants are describing the images using the same words, which suggests higher levels of coordination (Pickering and Garrod, 2004).[2]

Position of laughter

This is an independent variable which specifies whether the artificial laughter was added to the beginning or end of the message. Consider a message "this shape looks like a birthday cake". The turn-initial version is "*haha* this looks like a birthday cake". The turn-final version is "this shape looks like a birthday cake *haha*".

Next laughter

This variable records who produces the next natural laughter after an intervention. Possible values are: *Recipient* (if the next message containing a naturally produced *haha*

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[2] Note, there are many possible measures of alignment (lexical, syntactic, semantic) that can be analysed at different timescales (e.g., repetition in next turn vs. same game). Since we do not have specific predictions about short-term or long-term effects on syntactic vs. semantic alignment, we used the simplest measure.

is sent by the recipient of the artificial *haha*); *Sender* (if the next message containing a naturally produced *haha* is sent by the "spoofed" sender of the artificial *haha*); *None* (if the next message containing a *haha* is the next server intervention).

Hypotheses

H1 If written laughter is contagious, then participants in the manipulated condition, who are exposed to more laughter, should themselves produce more laughter (i.e. *haha*) and happy emojis.

H2 If written laughter contributes toward emotional contagion, manipulated participants' emotional state should be more positive.

H3 If written laughter contributes toward emotional contagion, the positive effect of written laughter on participants' emotions should lead to an increase in communicative involvement (i.e., to more characters typed), to better task performance (i.e., more successful rounds), and to more alignment.

H4 If message-final written laughter is used to signal that the current message contains the "laughable", then interventions containing message-final laughter should elicit more laughter from the recipient than interventions containing message-initial laughter.

Analysis

We analysed the results using R version 3.6.2 (R Core Team, 2017), together with the LME4 package version 1.1-26 (Bates, Maechler, Bolker and Walker, 2015). The models included random intercepts for dyads and participants. In addition to Manipulation (Control vs. *Haha*), the analyses also included Language (Dutch vs. English) as a predictor, in order to take into account possible differences between Dutch- and English-speaking groups. Akaike's Information Criterion (AIC) was used for model comparison, as there was no nesting relationship between all models being compared – so it was not possible to use a chi-square difference test between the different models. The model with the lowest AIC score was considered the best-fitting. Since we are interested in what the participants type, the artificial, transformed turns generated by the server are excluded from analysis; only the original, unmodified turns that are intercepted by the server are included in the analyses. We report the best-fitting model that contains the independent variable as well as the best-fitting model overall (see Table 1 below).

Table 1: Experiment 1. Inserting artificial haha in the Rorschach task. The table shows the best-fitting model (with lowest AIC) for each of the measures.

Dependent variables:

	Haha	Happy emoji	Task performance	No. of chars	Sentiment score	Alignment	Next *haha*
	logistic	*logistic*	*logistic*	*negative. binomial*	*linear*	*linear*	*logistic*
	lme4	*lme4*	*lme4*		*lme4*		*lme4*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fixed effects							
Language English = 0 Dutch = 1		-1.1** (-2.2, -0.1)	0.8*** (0.3, 1.3)	0.2** (0.001, 0.3)			
Intercept	-3.6*** (-3.9, -3.4)	-6.9*** (-8.1, -5.6)	2.3*** (1.9, 2.6)	7.5*** (7.4, 7.6)	0.1*** (0.05, 0.1)	-0.8*** (-0.8, -0.7)	-0.6* (-1.2, 0.05)
Random effects							
No. Participants	134	134			134		52
No. Dyads	67	67	67	67	67	67	28
SD Participants	0.874	1.81			0.023		1.812
SD Dyads	0.801	1.127	0.897	0.222	0.032	0.165	0

Observations	13,729	13,729	3,663	134	13,729	67	194
Log Likelihood	-2,253.0	-333.3	-860.8	-1,075.7	2,061.8	-253.0	-115.9
Akaike Inf. Crit.	4,511.9	674.6	1,727.6	2,159.3	-4,115.6	510.1	237.8
Note:	*lme4 = mixed model*						*p<0.1; **p<0.05; ***p<0.01

Results

Haha

A multi-level logistic regression did not show evidence that participants who receive artificially generated *haha*s produced more *haha*s. The best-fitting model excludes both the Manipulation and Language predictors. The. predicted probability of a mesage containing *haha* is 0.0256, 95% CI [0.0194, 0.0336].

Happy emojis

A multi-level logistic regression did not show evidence that participants who receive artificially generated *haha*s produce significantly more happy emojis. The best-fitting model excludes the Manipulation predictor, but includes Language (b = -1.1, SE= 0.534, z = -2.07, p= 0.039), suggesting that Dutch-speaking participants produce fewer happy emojis than English-speaking participants. The predicted probability of a message produced by Dutch speakers containing happy emojis is 0.000245, 95% CI [0.000086, 0.00139]. The predicted probability for English messages is 0.0010, 95% CI [0.000297, 0.00364].

Task performance

A multilevel logistic regression failed to show evidence that participants who receive artificially generated *haha*s perform better than participants in the control condition. The best-fitting model excludes the Manipulation predictor, but includes Language ($b = 0.804$, $SE= 0.269$, $z= 2.99$,$p = 0.00275$), suggesting that Dutch-speaking participants perform better than English-speaking participants. The predicted prob. of success for Dutch speakers is 0.956, 95% CI [0.935, 0.970]. The predicted prob. of success for English speakers is 0.907, 95% CI [0.873, 0.932].

Number of characters

A negative binomial regression failed to show evidence that participants who receive artificially generated *haha*s type more text than participants in the control condition. The best-fitting model excludes the Manipulation predictor, but includes Language ($b = 0.157$, $SE = 0.0795$, $z = 1.98$, $p = 0.048$), suggesting that Dutch-speaking participants type more text. The predicted number of characters for Dutch speakers is 2134, 95% CI [1899 – 2397]. The predicted number of characters for English speakers is 1823, 95% CI [1642, 2025].

Sentiment analysis

A multilevel linear regression failed to show evidence that participants who receive artificially generated *haha*s produce more positively valenced turns. The best-fitting model excludes both the Manipulation and Language predictors. The predicted sentiment score is 0.0593, 95% CI [0.05, 0.0687].

Alignment

A linear regression failed to show evidence that participants who receive artificially generated *haha*s align more than participants in the control condition. The best-fitting model excludes both the Manipulation and Language predictors. The predicted alignment score is 0.316, 95% CI [0.305, 0.328].

Producer of next *haha*

A multilevel binomial regression failed to show evidence that participants who received message-final *haha*s were more likely to produce *haha*s than participants who received turn-initial *haha*s. The predicted probability of the next naturally produced laughter being produced by the recipient of the artificial laughter is 0.644, 95% CI [0.488, 0.775].

Discussion

Surprisingly this experiment failed to show any effect of the interventions. We looked for and identified three possible factors. First, we asked participants for feedback. Two participants remarked that they noticed that the other participant was laughing too much and said that they ignored the laughter in order to complete the task. This might suggest that the server generated too many interventions (21 “spoof” *haha*s vs. 4 naturally occurring *haha*s). Therefore, perhaps fewer interventions might be more effective. Second, we became concerned that the interventions might be adding laughter to messages at moments in the unfolding interaction where laughter isn't warranted. Third, we noticed, by chance, that after the experiment was over, some participants continued chatting with each other in the app. These dialogues were much more spontaneous and were replete with *haha*s as well as *lol*s. This also suggests that these (non-)findings might be due to the task-oriented, competitive nature of the task. In order to take these concerns into account we conducted three more experiments.

5. Experiment 2: Inserting fewer *haha*s and *lol*s

Methods

This experiment used the same design as experiment 1, but the algorithm was adjusted to generate fewer interventions. Data was collected from two groups: (1) A group that received turns that had been prepended/appended with *haha*s, as in experiment 1. (2) A group that received turns that had been prepended/appended with *lol,* which were inserted with the same frequency as turns in group 1. Data from these two groups were compared with the control group from experiment 1. 26 dyads were collected in the *haha* condition, and 18 dyads were collected in the *lol* condition. Overall, participants in both conditions received 3.5 (S.D = 0.8) interventions over the course of the experiment. As with experiment 1, we report the best-fitting model with lowest AIC.

Hypotheses

The hypotheses are the same as in experiment 1.

H1 Participants who are exposed to more artificial laughter should themselves produce more laughter (i.e. *haha* or *lol*) and happy emojis.

H2 Participants who are exposed to more artificial laughter should produce turns with higher sentiment scores.

H3 Participants who are exposed to more artificial laughter should type more text, perform better in the task (i.e., more successful rounds), and align more.

H4 Interventions containing message-final laughter should elicit more laughter than interventions containing message-initial laughter.

Table 2: Experiment 2. Inserting artificial haha and lol in the Rorschach task. The table shows the best-fitting model (with lowest AIC) for each of the measures.

	Dependent variables:								
	Haha	Lol	Happy emojis	Task performance	Chars	Sentiment	Alignment	Next *haha*	Next *lol*
	logistic	*logistic*	*logistic*	*linear*	*negative binomial*	*linear*	*linear*	*logistic*	*logistic*
	lme4	*lme4*	*lme4*	*lme4*		*lme4*		*lme4*	*lme4*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Fixed Effects									
Haha	-0.1			0.2			0.03^{**}		
	(-0.6, 0.5)			(-0.3, 0.7)			(0.001, 0.1)		
Lol	-0.7^{**}			0.6^{**}			-0.00		
	(-1.3, -0.1)			(0.03, 1.2)			(-0.03, 0.03)		
Language				0.9^{***}	0.2^{***}	-0.03^{***}			
English=0				(0.4, 1.4)	(0.1, 0.4)	(-0.04, -0.02)			

Dutch= 1									
Intercept	-3.7***	-8.0***	-9.0***	2.1***	7.5***	0.02***	0.3***	0.05	-0.1
	(-4.0, -3.3)	(-9.8, -6.2)	(-11.5, -6.6)	(1.7, 2.5)	(7.4, 7.6)	(0.02, 0.03)	(0.3, 0.3)	(-0.7, 0.8)	(-1.1, 0.9)
Random effects									
No. Participants	156	156	156			156		37	
No. Dyads	78	78	78	78	78	78		24	7
SD Participants	0.842	2.636	3.351			0.012		1.282	
SD Dyads	0.731	0	0.479	0.736	0.232	0.022		0	0
Observations	15,976	15,976	15,976	4,305	156	15,976	78	57	15
Log Likelihood	-2,289.5	-312.7	-249.0	-1,121.3	-1,238.6	4,708.8	120.8	-38.4	-10.4
Akaike Inf. Crit.	4,588.9	631.3	503.9	2,252.6	2,485.2	-9,407.6	-233.7	82.7	24.7

Note: *lme4 = mixed model* *p<0.1; **p<0.05; ***p<0.01

Results

Haha

The best-fitting multi-level logistic regression model (see Table 2) failed to show evidence that participants who receive artificially generated *haha*s produce significantly more *haha*s (b = -0.0527, SE = 0.27705, z = -0.190, p = 0.849). However, the results show evidence that participants who received artificially generated *lol*s produced fewer *haha*s (b = -0.690, SE= 0.321, z = -2.149, p = 0.0317). The predicted probability of a message containing a *haha* in the control condition is 0.025, 95% CI [0.00175, 0.0356], while the predicted probability for messages produced by recipients of artificial *lol*s is 0.0127, 95% CI [0.00754, 0.0213].

Lol

The best-fitting multi-level logistic regression model only included the intercept, suggesting that participants who receive artificially generated *haha*s do not produce more *lol*s in response to *haha*s, and also do not produce more *lol*s in response to *haha*s (See table 2). The predicted probability of a message containing a *lol* is 0.000337, 95% CI [0.000057, 0.00199].

Happy emojis

The best-fitting multi-level logistic regression model only included the intercept, suggesting that participants who receive artificially generated *haha*s or *lol*s do not produce more happy emojis. The predicted probability of a turn containing a happy emoji is 0.00012, 95% CI [0.0000102, 0.00142].

Task performance

The best-fitting multi-level logistic regression showed no evidence of artificially generated *haha*s having an effect on task performance (b = 0.189, SE = 0.27, z = 0.72, p = 0.475). However, participants who received artificially generated *lol*s completed significantly more rounds (b = 0.595, SE = 0.289, z = 2.06, p = 0.0397). Dutch-speaking participants also completed significantly more rounds (b = 0.9247, SE = 0.261, z = 3.54, p < 0.001). The predicted probabilities of successfully completing a round are displayed in Table 3.

Table 3: Predicted probabilities of successfully completing a round (Experiment 2)

Manipulation	Language	Prob. success	95% *LL*	95% *UL*
Control	English	0.889	0.842	0.923
Haha	English	0.906	0.872	0.932
Lol	English	0.935	0.902	0.958
Control	Dutch	0.953	0.930	0.968
Haha	Dutch	0.961	0.931	0.978
Lol	Dutch	0.973	0.952	0.985

Number of characters

The best-fitting multilevel negative binomial regression only included the Language predictor, showing no evidence that the artificially-generated *haha*s or *lol*s influence the amount of text produced. However, the results suggest that Dutch-speaking participants type more text (= 0.216, *SE* = 0.0772, z= 2.82, p = 0.00507). The predicted number of characters typed by English-speaking participants is 1779, 95% CI [1635, 1935]. The predicted number of characters typed by Dutch-speaking participants is 2209, 95% CI [1947, 2505].

Sentiment analysis

The best-fitting multilevel negative binomial regression only included the Language predictor, showing no evidence that the artificially-generated *haha*s or *lol*s influence the sentiment of the messages. However, the results suggest that Dutch-speaking participants are more negative (*b* = -0.0293, *SE* = 0.006464, t= -4.53, p < 0.0001). The predicted sentiment score of Dutch messages is -0.00643, 95% CI [-0.0169, 0.00402]. The predicted sentiment score of English messages is 0.02287, 95% CI [0.0157, 0.030].

Alignment

The best-fitting linear regression shows evidence that participants who receive artificially generated *haha*s align more than participants in the control group (*b* = 0.0281, *SE* = 0.0137, t = 2.06, p = 0.043). However, there was no evidence of any effect of *lol*s on alignment (*b* = -0.0002476, *SE* = 0.0153, t = -0.016, p = 0.987). The predicted alignment score of dyads in the control group is 0.319, 95% CI [0.301, 0.336]. The predicted alignment scores of dyads who receive *haha*s is 0.347, 95% CI [0.326, 0.367].

Producer of next *haha*

The best-fitting multilevel binomial regression failed to show evidence that participants who received message-final *haha*s were more likely to produce *haha*s than participants who received turn-initial *haha*s. The predicted probability of the next naturally produced *haha* being produced by the recipient of the artificial laughter is 0.488, 95% CI [0.310, 0.669]. Due to convergence issues, simplified models were used that did not include the random slope of laughter position (message-initial vs. message-final) for participants. Also, due to convergence issues, the analysis excluded the most complex model with an interaction effect (laughter-position x language).

Producer of next *lol*

The best-fitting multilevel binomial regression failed to show evidence that participants who received message-final *lol*s were more likely to produce *lol*s than participants who received turn-initial *lol*s The predicted probability of the next naturally produced lol being produced by the recipient of the artificial laughter is 0.533, 95% CI [0.293, 0.759]. Due to convergence issues, simplified models were used which only included an intercept for each dyad. Also due to convergence issues the analysis excluded the most complex model with an interaction effect (laughter-position x language).

Discussion

Although we found no evidence of overt copying of *haha*s or of *lol*s, the results suggest that participants were not ignoring the interventions. Strikingly, dyads who received artificially generated *lol*s produced fewer *haha*s and performed better in the task. This indicates that in text-mediated communication *lol* patterns differently from *haha* and therefore cannot be considered as a variant of *haha* (see, e.g., McSweeney, 2016 and Section 1.2.1 above). Yet despite there being no observable effect of artificially generated *haha*s on the production of *haha* or *lol*, dyads who received artificially generated *haha*s aligned more with each other, suggesting that both types of intervention had an overall effect on coordination.

6. Experiment 3: Inserting laughter in next turn

This experiment addresses two concerns raised by Experiment 1. The first concern was that the task-oriented competitive nature of the dialogue might be discouraging participants from adopting a "non-serious" frame, thereby inhibiting the production of *haha*s and *lol*s, as well as inhibiting the emotion "transfer" between participants. This was addressed by using a different task. The second concern was that the *haha*s were inserted infelicitously in turns, perhaps making it appear to the recipient that the spoofed sender is laughing inappropriately at their own turn or at the turn of their partner. To address this concern the algorithm was adjusted to only manipulate specific turns.

Methods

The balloon task

In this experiment participants engage in the balloon task, in which participants need to discuss a moral dilemma and come to a joint decision: A hot air balloon with three participants is rapidly losing height. In order for two of the occupants to survive, one occupant must jump out (or be pushed!) out of the balloon to a certain death. The three occupants are: The balloon pilot; A scientist who has discovered an important cure for cancer; The scientist's wife, who is pregnant. Previous research has shown that this leads to lively, spontaneous, open-ended conversation (Healey et al, 2003). In this task, pairs of participants were instructed to discuss this scenario for 10 minutes and then come to a decision. Due to corona restrictions, participants participated remotely, using the app on their mobile phone.

Manipulation: inserting *haha*

Instead of inserting artificial laughter in random turns throughout the interaction, the experiment only inserted *haha*s in turns that followed naturally occurring *haha*s. The server analysed all turns for *haha*. If the server detected a *haha* produced by a participant, the server would intercept the next turn produced by the other participant (i.e., the recipient of the naturally produced *haha*). If this turn did not already contain a *haha*, the server would add a *haha* to that turn. For example:

(1)	**P1:**	I think we should throw out the useless pilot *haha*
(2)	**P2:**	They don't need a pilot. Let the scientist fly the balloon. *(Actual turn, sent by participant, intercepted by server)*
(3)	**P2:**	*Haha* they don't need a pilot. Let the scientist fly the balloon *(Artificial turn, received by participant 1)*

Example 2: Artificial laughter inserted in next turn

This manipulation is intended to give participants the illusory impression that their partner laughs after they laugh, i.e., giving the impression that their laughter is "contagious".

Hypotheses

The hypotheses are the same as in the previous two experiments.

H1 Participants who are exposed to more artificial laughter should themselves produce more laughter (i.e., *haha* or *lol*) and happy emojis.

H2 Participants who are exposed to more artificial laughter should produce turns with higher sentiment scores.

H3 Participants who are exposed to more artificial laughter should type more text and align more.

H4 Interventions containing message-final laughter should elicit more laughter than interventions containing message-initial laughter.

Data analysis

Since the intervention is only triggered if participants actually produce *haha*s, 4 dyads that did not produce any *haha*s were excluded from analysis. This resulted in 34 dyads in the control group and 30 dyads in the manipulated group. Participants in the experimental condition received on average 5.7 (SD = 4.6) interventions. We report the best-fitting model that contains the independent variable as well as the best-fitting model overall (see Table 4 below).

Table 4: Best-fitting models in Experiment 3. Inserting artificial haha in response to natural haha in the balloon task. The table shows the best-fitting model (with lowest AIC) for each of the measures

	Dependent variables:						
	Haha	Lol	Happy emojis	No. chars	Sentiment	Alignment	Next *haha*
	logistic	*logistic*	*logistic*	*negative binomial*	*linear*	*linear*	*logistic*
	lme4	*lme4*	*lme4*	*lme4*	*lme4*		*lme4*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fixed effects							
Haha	-0.4***						
	(-0.8, -0.1)						
Language			-1.2***	0.2	-0.05***	0.03**	-1.0
English = 0			(-1.8, -0.6)	(-0.03, 0.3)	(-0.1, -0.03)	(0.01, 0.05)	(-2.3, 3.0)
Dutch = 1							
Intercept	-2.1***	-6.2***	-3.4***	6.9***	0.1***	0.2***	1.8***
	(-2.3, -1.9)	(-7.3, -5.0)	(-3.9, -2.9)	(6.8, 7.1)	(0.1, 0.1)	(0.2, 0.2)	(0.7, 2.9)
Random effects							

No. Participants	128	128	128		128		36
No. Dyads	64	64	64	64	64		25
SD Participants	0.498	0	0.945		0.034		0
SD Dyads	0.369	0.748	0.525	0	0		0.763
Observations	5,225	5,225	5,225	128	5,225	64	109
Log Likelihood	-1,708.1	-96.8	-599.8	-952.4	-629.0	117.6	-60.8
Akaike Inf. Crit.	3,424.2	199.6	1,207.7	1,912.8	1,268.1	-229.2	129.7
Note:	*lme4 = mixed effects*						*p<0.1; **p<0.05; ***p<0.01

Results

Hahas

A multilevel logistic regression showed that participants who received artificially generated *haha*s produced significantly fewer *haha*s than participants in the control group (b = -0.447, SE = 0.164, z = -2.73, p = 0.00625). The predicted probability of a message containing *haha* is 0.109, 95% CI [0.09, 0.132] in the control condition and 0.0728, 95% CI [0.0577, 0.0915] for messages produced by participants who receive artificially generated *haha*s.

Lol

The best-fitting logistic regression included only the intercept, suggesting no effect of artificially generated *haha*s on the production of *lol*s . (Due to convergence problems, the models only included intercepts for dyads, not for participants). The predicted probability of a message containing *lol* is 0.0021, 95% CI [0.00065, 0.00652].

Happy emojis

The best-fitting multilevel logistic regression only showed an effect of language. Dutch-speaking participants produced fewer happy emojis than English-speaking participants ($b = -1.168$, $SE = 0.311$, $z = -3.75$, $p < 0.001$). The predicted probability of Dutch messages containing a happy emoji is 0.0102, 95% CI [0.00642, 0.0161]. The predicted probability of English messages containing a happy emoji is 0.032, 95% CI [0.02, 0.0510].

Number of characters

The best-fitting multilevel negative binomial regression includes Language as predictor, although it failed to reach significance ($b = 0.158$, $SE = 0.0965$, $z = 1.64$, $z= 0.101$). The model predicts Dutch speakers typing 1214 characters, 95% CI [1087, 1357] characters. The model predicts English speakers typing 1036 characters, 95% CI [889, 1208].

Sentiment analysis

The best-fitting multi-level linear regression shows no evidence of artificially-generated *haha*s influencing the sentiment of participants' messages. However, the model shows an effect of language: Dutch-speaking participants are more negative ($b = -0.047$, $SD = 0.011$,

$t = -4.47$, $p < 0.001$). The model predicts a sentiment score of 0.108, 95% CI [0.0914, 0.1254] for English messages, and a sentiment score of 0.0613, 95% CI [0.0496, 0.0729].

Alignment

The best-fitting linear regression shows no evidence of artificially-generated *haha*s influencing the sentiment of participants' messages. However, the model shows an effect of language: Dutch-speaking participants aligned more ($b = 0.0258$, $SE = 0.01$, $t = -0.006$, $p = 0.995$). The model predicts an alignment score of 0.223, 95% CI [0.206, 0.24] for English-speaking dyads and an alignment score of 0.249, 95% CI [0.237, 0.261] for Dutch-speaking dyads.

Producer of next *haha*

The best-fitting multilevel binomial regression failed to show evidence that artificially generated message-final *haha*s elicited more *haha*s from the recipient of the intervention. The best-fitting model includes Language as a predictor, which failed to reach significance ($b = -0.978$, $SE = 0.66$, $z = 1.48$, $p = 0.138$). The predicted probability of a turn-final *haha* being followed by a *haha* from the recipient as opposed to the spoofed sender is 0.858, 95% CI [0.658, 0.950] for English-speaking dyads, whereas for Dutch-speaking dyads the predicted probability is 0.694, 95% CI [0.538, 0.816].

Discussion

This experiment found no support for H1, H2 or H3. Although the artificially generated *haha*s had an effect on the production of laugh particles, this effect is inhibitory, which works against the basic predictions of the "emotional contagion" account. We explore this in more detail in the general discussion, below in Section 3.

7. Experiment 4: Removing *haha*

There is still the concern that the interventions in experiment 1-3 are not ecologically valid. The laugh particles are added to turns that are designed without laughter. Further, the laugh particles are crudely prepended or appended to turns without taking into account the preceding dialogue. In order to sidestep this issue, this experiment uses a method similar to Liebman and Gergle (2006) of filtering out laugh particles (instead of inserting them). As in experiment 3, participants completed the balloon task, for class credit. This task was conducted solely in English in an international class, remotely due to corona restrictions.

Methods

Manipulation

Participants were assigned to either a control group or to a manipulated group. In the manipulated group, participants' messages were intercepted by the server. If a turn contained a variant of *haha (*e.g. *hah*, *hahha*, *hahaha*, *ahahahaha*, etc.) the variant was excised from the turn, and the modified turn was sent to the other participant. Thus, if a participant typed the turn "let's chuck out the pilot *haha*", the other participant would receive the turn "let's chuck out the pilot".

Hypotheses

H1 If written laughter is contagious then excising *haha*s from the dialogue will create fewer opportunities for contagion and consequently lead to participants producing fewer turns containing *haha* and fewer happy emojis than in the control group.

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H2 If written laughter contributes toward emotional contagion in CMC then participants in the manipulated group should produce turns with lower sentiment scores.

H3 If written laughter contributes toward emotional contagion in CMC then positive contagion in the manipulated group will be inhibited, resulting in participants being less engaged with each other, expend less effort in the discussion, and consequently write fewer characters and align less with each other

Note that this experiment does not allow testing of hypothesis 4 (concerning the effect of *haha*-placement), since *haha*s are excised from the dialogue.

Analysis

The analyses compare a model that contains the independent variable with a nested simpler model using a likelihood ratio test. 15 dyads were excluded from analysis because neither member of the dyad produced a *haha*, yielding 10 control group dyads and 17 manipulated dyads. In addition, the data from each dyad prior to the first *haha* were discarded, since prior to the first *haha* there would be no opportunity for contagion to take place.

Table 5: Best-fitting models for experiment 4. Removing haha from turns in the balloon task. The table shows the best-fitting model (with lowest AIC) for each of the measures

Dependent variables:

	Haha	Lol	Happy emojis	No. chars	Sentiment score	Alignment
	logistic	*logistic*	*logistic*	*Negative binomial*	*linear*	*linear*
	lme4	*lme4*	*lme4*	*lme4*	*lme4*	
	(1)	(2)	(3)	(4)	(5)	(6)
Fixed effects						
Intercept	-2.4^{***}	-5.0^{***}	-4.8^{***}	6.0^{***}	0.1^{***}	0.2^{***}
	(-2.7, -2.1)	(-5.9, -4.2)	(-6.1, -3.6)	(5.8, 6.2)	(0.1, 0.1)	(0.2, 0.2)
Random effects						
No. Participants	54	54	54		54	

No. Dyads	27	27	27	27	27	
SD Participants	0.299	0	1.089		0.017	
SD Dyads	0	0	1.043	0.468	0	
Observations	771	771	771	54	771	41
Log Likelihood	-222.8	-30.2	-73.5	-354.3	-91.3	50.2
Akaike Inf. Crit.	451.7	66.4	152.9	714.6	190.6	-96.4
Note:						*p<0.1; **p<0.05; ***p<0.01

Results

Hahas

A multilevel logistic regression failed to show an effect of removing *haha*s on the production of *haha*s. A likelihood ratio test of the model with the manipulation effect against the model without manipulation effect did not reveal a significant difference ($\chi 2$ (1) = 0.252, p = 0.616). The predicted probability of a message containing *haha* is 0.122, 95% CI [0.0966, 0.152]. (Note that these *haha*s are not relayed to the other participant, however they are captured by the server and are available for analysis).

Lols

A multilevel logistic regression failed to show an effect of removing *haha*s on the production of *lol*s. A likelihood ratio test of the model with the manipulation effect against the model without manipulation effect did not reveal a significant difference ($\chi 2$ (1) = 2.27, p = 0.132). The predicted probability of a message containing *lol* is 0.0375, 95% CI [0.00264, 0.0148].

Happy emojis

A multilevel logistic regression failed to show an effect of removing *haha*s on the production of happy emojis. A likelihood ratio test of the model with the manipulation effect against the model without manipulation effect did not reveal a significant difference ($\chi 2$ (1) = 0.0655, p = 0.798). The predicted probability of a message containing a happy emoji is 0.00881, 95% CI [0.00662, 0.0378].

Number of characters

A multilevel negative binomial regression failed to show an effect of removing *haha*s on the number of characters produced. A likelihood ratio test of the model with the manipulation effect against the model without manipulation effect did not reveal a significant difference ($\chi 2$ (1) = 0.140, p = 0.708). The predicted amount of text produced by each participant is 368 characters, 95% CI [290, 466].

Sentiment analysis

A multilevel linear regression failed to show an effect of removing *haha*s on sentiment of the turns. A likelihood ratio test of the model with the manipulation effect against the model without manipulation effect did not reveal a significant difference ($\chi2$ (1)= 0.0031, p = 0.96). The predicted sentiment score is 0.108, 95% CI [0.0836, 0.133].

Alignment

A linear regression failed to show an effect of removing *haha*s on lexical alignment. A likelihood ratio test of the model with the manipulation effect against the model without manipulation effect did not reveal a significant difference (F (1,39) = 0.461, p = 0.501). The predicted alignment score is 0.197, 95% CI [0.174, 0.22].

Discussion

This experiment found no support for H1, H2 or H3.This is surprising as the experimental manipulation should result in more naturalistic interventions than the previous three experiments. It is also surprising since this method of removing cues from turns did have a measurable effect on the dialogue in experiments conducted by Liebman and Gergle (2016). One possible reason could be that Liebman and Gergle instructed participants prior to the task that they could and should use the various cues that were being artificially excised from the messages. We didn't provide participants with these, in our view, potentially confounding instructions, which possibly also resulted in more dyads needing to be discarded, since they produced no *haha*s at all. We return to this experiment in the general discussion, below.

8. General Discussion

Overall, there is very little support for contagion theories.

H1, regarding behavioural mimicry, proposed that written laughter is contagious. However, we found no evidence for verbatim mimicking of written laughter: Exposing participants to an increased number of *haha*s did not increase their own use of *haha* (experiment 1 and 2). Similarly, exposing participants to an increased number of *lol*s did not increase participants' use of *lol* (experiment 2), while decreasing participants' exposure to *haha*s did not lead to a corresponding decrease in the use of *haha*s. Prima facie, experiment 3 even provides evidence of an inhibitory effect, as participants who were exposed to *hahas* produced fewer *hahas*. There is, however, weak support for non mimicry-based contagion: in experiment 2, participants who had been exposed to more *lol*s produced more *haha*s.

There was no support for H2, which predicted that laugh particles would increase positive sentiment. The sentiment scores were not affected by the manipulations of all four experiments.

Yet, despite there being no discernible effect on participants' emotional language, there was some evidence for H3, the assumption that introduction of fake laugh particles will have positive effects in the participants' performance: the interventions affected interpersonal coordination. In experiment 2, increasing participants' exposure to *lol*s leads to better task performance, while adding *haha* leads to more lexical alignment.

There is also no support for H4: no evidence was found that the position of the laughter-particle (message-initial vs. message-final) affects whether the message elicits laughter or not.

Taking a step back and viewing the results from the set of the 4 experiments as a whole, makes the general contagion account even less plausible: Participants in experiment 1 were exposed to more written laughter than participants in experiment 2, who in turn were exposed to more written laughter than participants in experiment 3, while participants in experiment 4 were exposed to even less laughter – the latter were exposed to no written *haha*s at all. The most fundamental prediction of any model of contagion is that more exposure should lead to more contagion. Yet no such gradient is observed for any of the dependent variables across experiments 1,2,3,4.

Across the four experiments there were a few cross-linguistic differences. First, experiment 2 showed that Dutch-speaking participants performed better at the Rorschach task than English-speaking participants. In our view, the most plausible explanation for this difference is that, since the research was conducted in the Netherlands, it is likely that the English-speaking groups comprise exchange students from many different academic and cultural backgrounds, some of whom might also be speaking in their second language. Also, experiments 1 and 3 found that Dutch-speakers use fewer happy emojis than English-speakers, however the heterogeneity of the English-speaking groups makes it difficult to draw any broader conclusions without also examining the patterns of all emoji use (not simply happy emojis), supported by fine-grained qualitative analysis. It is possible that the difference in sentiment scores parallels the patterns of emoji use, however, this effect could simply be due to differences in sensitivity of the Dutch and English sentiment toolkit packages. Most importantly, despite these differences, none of the best-fitting models include a Language x Intervention interaction, providing no evidence that English and Dutch speakers might be responding differently to the interventions.

These (non-)findings highlight the inadequacy of psychological and neuroscientific accounts whose explanatory means involve behavioural mimicry and emotional contagion. In these accounts, laughter is treated as the outward expression of pre-existing internal states. A participant might find something amusing and laugh. Their conversational partner is then more likely to mimic this behaviour automatically and laugh more, leading to contagious laughter behaviour and subsequently contagious emotional states. This view stems from a rather naive treatment of laughter, which ignores its rich, highly contextualized function – both in online and offline interaction. From our experiments, it does not seem to be the case that laughter is perceived as an instinctive, uncontrolled reaction to some stimulus. Therefore, we believe that the more sophisticated analyses of laughter, the linguistic analysis and the conversation analytic findings about the nature of laughter in interaction, suggest further reasons why we didn't find straightforwardly interpretable results in these experiments.

First, as we said earlier, Ginzburg et al.'s (2015, 2020) analysis of laughter does not assume that placement of laughter is strictly associated with its reference. The laugh particle can follow the 'laughable' or anticipate it or, even, indicate search of the context for it. This might explain why H4 did not yield the expected results: laughter recipients are free to associate the laughter with any event that seems most appropriate as the antecedent laughable event and laughter position does not determine this antecedent. Moreover, this linguistic analysis considers laugh particles as word-like with their own lexical entries. This means that they are associated with semantics and they are assumed to perform independent speech acts like assertions regarding the speaker's emotional state or assertions about the speaker's perception of some incongruity in the context. This individualistic analysis is therefore compatible with the lack of finding any mimicry effects among participants since there is no assumption that laugh particles either automatically or strategically invite the other participant to laugh too, thus explaining the lack of contagion findings under H1-H3.

However, this linguistic theory also predicts considerable processing effort in resolving laughter reference involving obligatory lexical disambiguation, anaphora resolution, and pragmatic reasoning to accommodate the contribution of laugh particles in the dialogue information state. Otherwise, dialogue coherence, implemented in the formalisation of the 'grounding' process (Clark, 1996) in the model, is under threat. Nevertheless, in the current study, even a substantial amount of randomly introduced written laughter, which cannot by assumption either find an antecedent or perform a felicitous speech act, did not induce any negative effect. Neither did the removal of laugh particles cause any problems as far as our measures show. It would be predicted that arbitrarily introducing or removing indexical elements, as laugh particles are assumed to be under this analysis, would cause considerable effort and frustration to resolve them, with a negative effect on task success. However, the participants in some cases seemed to simply ignore them (Experiment 1). It is conceivable that participants simply ignored the random laughter interventions since they were incoherent with the current context. Indeed, a consistent finding in studies of face-to-face and mediated interaction is that participants frequently and unproblematically ignore each other's turns, especially when they are incoherent (Healey, et al., 2003; Galantucci and Roberts, 2014; Roberts et al., 2016; Galantucci et al., 2014). In the CA-related literature this has been termed the 'let it pass' strategy (Cicourel, 1973; Firth, 1996). However, this strategy is not available under this model because every utterance received with explicit semantics and pragmatic contribution needs to be grounded and if grounding is unsuccessful it should trigger a clarification sequence until it is resolved. This should have caused delay and disruption in the manipulated interactions leading to the participants performing worse than the control group. But we did not find any such effects. Moreover, 'let it pass' cannot be the whole explanation because, instead of causing trouble or just being ignored, in Experiment 2 the randomly introduced *lol*s improved performance while the *haha*s increased lexical alignment.

It then seems that a more subtle explanation of how laugh particles function might be needed. Instead of specifying what laugh particles mean, we could examine what such particles do in interaction. In contrast to the linguistic analysis of laughter tokens as words employed in assertions about propositions and individual emotional states, work in Conversation Analysis (CA) assumes that laughter, even though it is meaningful, lacks encoded semantic propositional content (Glenn, 2003). From this perspective, one could assume that non-verbal signals are presented as offers for joint conversational actions ('affordances', see also Ham, this volume) whose status and import needs to be negotiated and ratified by the other participants if it is to have an effect in the interaction. Following the 'let it pass' strategy, we believe that the experiments here provide evidence that laughter recipients can choose not to take up signals that do not make sense to them without breaking down any rigidly defined process of 'grounding'. Given that such signals and their imports need to be negotiated to become fully specified as full-fledged signs, recipients need not consider the consequences of not pursuing them.

This could explain why overwhelmingly participants appear to be ignoring the interventions in experiments 1-3. What remains to be explained is why recipients of fake laughter might perceive it as incoherent and choose to ignore it in their verbal behaviour while it has effects in some measures of coordination as in Experiment 2. First, as described in section 2.1 above, the significance of laughter in f-t-f communication is negotiated and jointly determined by the participants. Since, under this framework, participants cannot rely on encoded contents associated with specified lexical entries for laughter, in order to successfully accomplish an invitation to laugh, participants need to recruit a combination of multiple resources fitting a precisely organised sequential placement and turn design (see e.g., Glenn & Holt, 2013). As we said, this might seem not to hold for written language where there is a more clear and permanent record of laughter than in the fleeting context of verbal interaction. But this is not the case, because having a written record of the conversation history does not obviate the need for a synergy of resources for perceiving an element as a laughter invitation: a laughter invitation is not just an action undertaken by the individual speaker but needs to become a joint affordance in the context of the interaction. Affordances are relational properties involving not only the speaker-hearer dyad but also the sociomaterial environment of the interaction (Chemero, 2009; Rietveld et al., 2018; Gregoromichelaki et al, 2020), for example, in our cases, the fact that participants are not co-present, the affordances of the task, the time constraints, the stimuli, task-specific actions, like the selection of /*same* or /*different*, the particular appearances of the various laugh particles and the devices and interfaces through which the communication takes place.

In that respect, the placement of the laugh particles by the algorithm is extremely crude. Experiments 1 and 2 simply select random turns for adding artificial laughter, and the algorithm randomly chooses whether to prepend or append the laughter. As a result, the recipients of the interventions most likely could not interpret the manipulated turns as responding to or inviting laughter, as the necessary sociomaterial resources do not support the fake laugh particles. This suggests that, even in text-mediated environments where what has been transmitted is a matter of public record, a signal that is not perceived as meshing with joint affordances cannot be imposed as a sign just because an individual speaker's utterance introduced it obliging recipients to process it; instead, even the status of such a signal as a sign is an interactional achievement co-constituted by both interlocutors (see, e.g., Gregoromichelaki et al., 2011; Rączaszek-Leonardi et al, 2014; Gregoromichelaki and Kempson, 2015; Mills, 2017).

Second, although the interventions in experiment 3 were marginally sensitive to the context, the fact that laughter is typically invited and accepted (or declined), as opposed to simply being a contagion effect that is transmitted via exposure, suggests why the inventions seemed to be having an inhibitory effect on laughter. According to Jefferson (1979), when an invitation to laugh is received, it is not adequate for a recipient to simply not laugh in order to decline the invitation. Such non-action may motivate further attempts to trigger the shared laughter. Instead, a participant must attempt to deflect the shared laughter attempt by, for example, speaking seriously and switching the relevance of the response towards topics that have been raised in the turn containing the invitation for shared laughter. Such deflection might be what has been perceived in experiments 1 and 2 since the competitive nature of the task created a strong pressure for topical contributions. Therefore, a plausible explanation of what is happening in experiment 3 is that the artificial interventions, which are positioned immediately after naturally occurring laughter, are treated by the recipient of the intervention as acceptance of the invitation to laugh, thereby leading the recipient of the intervention to relinquish further pursuit of laughter, since the projected action of laughing was apparently successful.

Third, as we said earlier, the fact that an invitation to laughter often occurs accompanied with other linguistic, semantic, and pragmatic cues perhaps suggests why no difference was found in experiment 4, where all *haha*s were removed from the dialogue. Consider Transcript 1 below from experiment 4 which shows “simultaneous” laughter even though neither participant can see the other’s laugh particle:

1	P30	I mean with susie you save two people	
2	P30	But the scientist may again save people with his research	
3	P30	What do you think?	
4	P29		I am trying to think of another way... because it will not be fair to throw someone based of his health situation or occupational situation
5 (blocked)	P29		But I don't know how *haha*
5 (sent to P30)	P29		But I don't know how
6 (blocked)	P30	*Haha* yeah that would be a better solution	
6 (sent to P29)	P30	Yeah that would be a better solution	
7	P30	I mean the balloon pilot also may be the only one	

	able to pilot the balloon to safety

Transcript 1: Dialogue from experiment 4 which filters out all naturally produced haha*s. Notice how, in line 5, P29's* haha *is removed from the turn. Despite laughter being filtered out, the next turn by P30, which is produced in response to P29's turn, also contains written laughter*

This suggests that, since other relevant cues have been assembled in the context, the overt presence of the inviting laugh particle is not as significant for the laughter response to occur (i.e., there is redundancy in the informational sense in the signalling of laughter invitation). The effect of the inviting laugh particle is supported by a synergy of a host of other strategically planned interactional elements and, for this reason, its lack does not necessarily cancel the expected response (see e.g., Glenn & Holt, 2013; cf Fischer et al., this volume). This can also explain the implicit effects that the presence of *lol*s and *haha*s had in Experiment 2.

In any case, given these results, it is difficult to know what is going on without engaging in detailed qualitative analysis of each of the interventions, which we suggest as potential future research.

9. Conclusions and future work

The (non-)findings of the 4 experiments are consonant with the growing body of work that suggests that the notions of automatic mimicry, copying, priming, repetition, alignment or contagion, even though important, are not adequate for explaining human-human coordination (Fusaroli et al., 2014; Hodges, 2014; Mills, 2011; Mills, 2014; Koudenburg et al., 2015; Fischer, 2016; Fusaroli and Tylen, 2016; Hale & Hamilton, 2016; Strupka et al., 2016; Kindermann & Skinner, 2019; Zhang & Healey, 2018; Chivers, 2019; Reed, 2020; cf. Sherman & Rivers, 2021; see also Lelonkiewicz et al., 2021).

The findings also suggest that the experimental design we used in experiments 1-3, i.e., that of inserting numerous *haha*s throughout the interaction with little or no context-sensitivity was ill-suited for investigating the communicative function of laugh particles.

However, the technique of AI-mediated communication offers much more sophisticated forms of experimental design. The approach of Liebman and Gergle (2016) of filtering out all cues can be fine-tuned to selectively filter out specific cues. For example, to address the question whether turn-final *haha*s are used more to invite laughter than turn-initial *haha*s, it would be possible to selectively filter out only one of these types of laughter and examine the effect on recipients' laughter invitations and acceptances. In addition to filtering out cues to test their effect on interaction, or inserting artificial cues as in experiments 1-3, Transformed Social Interaction can be used to automatically detect and then modify cues, in real-time: Turn-initial *haha*s can be transformed into turn-final *haha*s, and vice-versa. Similarly, to investigate possible differences between *lol*s and *haha*s, both types of written laughter could be detected and automatically swapped. This technique also lends itself to amplifying laughter, e.g., by artificially lengthening “haha” to “hahahaha”, by swapping to upper case (“HAHA”), by inserting punctuation, e.g. (“haha!”) or detecting and repeating punctuation (e.g., changing “haha!” to “haha!!!!”) (Kalman and Gergle, 2014; Sidi et al., 2021). These techniques ensure ecological validity in that the laugh particle is positioned at a location in the message where a participant actually produced written laughter.

In our opinion it would be fruitful to complement this approach with a different type of chat interface which displays participants’ typing in real-time. These character-by-character interfaces are associated with greater interpersonal co-ordination and emotional synchrony (Ziembowicz and Nowak, 2019); participants can respond instantly to each other as the interaction unfolds, and crucially this mutual responsivity can be experimentally manipulated at an extremely fine grain (Maraev et al., 2020).

10. References

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