EMOTIONAL CONTAGION THROUGH ONLINE NEWSPAPERS

Research paper

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Abstract

Emotions spread through online and offline social networks and subsequently influence individuals' decisions and behaviours. Empirical studies on emotional contagion are almost non-existent in information systems research, leaving a gap in understanding how individuals are affected by emotions expressed in online sources. Online newspaper articles and the associated readers' comments provide a rich and mostly unfiltered data source that is utilized in this work to identify emotional contagion effects between newspaper publishers and its readers. By applying lexicon-based sentiment analysis and multilevel linear regression models to 1,151 online newspaper articles and 28,948 associated readers' comments, we model the relationships between sentiments in newspaper articles and comments. The results provide empirical support for emotional contagion effects between emotions expressed in online newspaper articles and emotions expressed in readers' comments. Linguistic, psychological and methodological limitations are considered and discussed.

Keywords: Emotional Contagion, Sentiment Analysis, News, Web 2.0.

1 Introduction

The emergence of the Web 2.0 allows users to create content and interact online (Chau and Xu, 2012). By doing so, not only information, but also emotions can spread through the Internet (Chau and Xu, 2012; Pang and Lee, 2008). Researchers have shown, for example, that emotions can travel through the news feeds of online social networks. In a field experiment on Facebook, Kramer et al. (2014) secretly manipulated the news feeds of almost 700,000 users by filtering out messages with high emotional content in order to test if this has an effect on the emotions expressed in their own posts. The results showed that when messages with positive emotions were removed, users subsequently posted less positive and more negative messages. The opposite happened when the number of messages with negative emotions was reduced.

Online social networks like Facebook afford various interaction possibilities, for example, sharing multimedia content, connecting or following other users, and commenting and liking posts from others. These affordances can facilitate the spreading of information and emotions. For example, as people tend to connect with similar others within a network (McPherson 2001) and most recommendation and filtering algorithms employed by social network providers are based on the concept of similarity (Pariser 2011), they are more likely to be exposed to content that is in line with their own opinions and, in turn, more likely to positively react to this content. In this study, we investigate if and how emotions can be transmitted through less interactive Web 2.0 applications, namely online newspapers. More than 90% of newspaper publishers provide articles online and many allow readers to interact with the publishers (Santana, 2010; Singer and Ashman, 2009). Yet, in contrast to online social networks the interaction possibilities on online news websites are much more limited and often reduced to commenting on articles (peer-to-peer interactions and communication are typically not allowed). Against this background, our study addresses the following research question: Can emotions spread from online newspaper articles to readers' comments? This question is of high scientific and practical interest, as it has been observed that the tone of news steadily became more negative over the last decades (Pinker 2018). Even if negative emotions expressed in news may only have a small influence on a human's overall emotional state, online newspapers have millions of readers and, hence, these small individual effects can add up (or even multiply) to a quite large overall effect at the population level. News websites can be understood as information systems (IS) at both the individual and group level (Sidorova et al. 2008) and, hence, gaining a better understanding about their design, use, and consequences is a relevant objective for IS research and practice. For example, a mindful and responsible design of news websites (e.g., by deploying recommendation algorithms that are based on diversity instead of similarity) could help to avoid possible unintended consequences of their use, such as, the unconscious spreading of negative emotions among users. And as happiness, or a lack thereof, has been shown to have a strong influence on people's wellbeing and health (Fowler and Christakis, 2008), potential emotional contagion through online news has also implications for various research streams beyond information systems, such as, psychology, sociology, medicine, and others.

Our work is based on Emotional Contagion Theory (Hatfield et al., 1994), which defines emotional contagion as "a process in which a person or group influences the emotions or behaviour of another person or group through the conscious or unconscious induction of emotion states and behavioural attitudes" (Schoenewolf, 1990, p. 50). Empirical studies drawing on Emotional Contagion Theory suggest that behaviours, such as smoking (Christakis and Fowler, 2008) or eating (Christakis and Fowler, 2007), as well as emotions (Fowler and Christakis, 2008; Kramer et al., 2014) spread through offline and online social networks via peer-to-peer contagion. Based on the theory, we derive three hypotheses capturing first the overall effect of emotional contagion through online newspaper articles. Secondly, we analyse within-emotional effects, namely the influence of positive (negative) emotions on positive (negative) emotions. Thirdly, cross-emotional effects - the influence of positive (negative) emotions on negative (positive) emotions – are investigated. We then apply dictionary-based sentiment analysis to measure emotions in more than 1,000 newspaper articles and about 30,000 associated readers' comments, which were collected through a Web 2.0 widget placed within the articles of a major German newspaper. Accordingly, the German version of the Linguistic Inquiry and Word Count (LIWC) dictionary (Pennebaker et al., 2001; Wolf et al., 2008) was used to measure sentiment scores for both online newspaper articles and readers' comments. Finally, we apply multi-level linear regression models to test the developed hypotheses using the collected data.

Overall, we find empirical evidence for the spreading of emotions from newspaper articles to readers' comments. For example, an increase in positive emotions expressed in newspaper articles leads to an increase in positive emotions in the associated readers' comments. Similar effects were observed for newspaper articles exhibiting negative emotions. Yet, we could not find evidence for so-called cross-emotional effects, for example, that an increase in positive emotions in newspaper articles leads to a decrease in negative emotions in comments.

The remainder of this paper is structured as follows. First, we provide theoretical background on Emotional Contagion Theory, review extant empirical studies in the field, and develop our research hypotheses. Next, we describe our dataset and analysis methods. Subsequently, we present and discuss our empirical findings. The paper concludes with a short summary and outlook on further research.

2 Theoretical background

Emotional contagion describes the conscious and unconscious influence of peers' emotions on an individual (Hatfield et al., 1994; Schoenewolf, 1990). These emotions are either positive or negative, triggering individuals to approach or withdraw from a certain situation (Hatfield et al., 1994). Fischer et al. (1990) provide a more distinct perspective on emotional dimensions, stressing that positive and negative emotions are the first level of an emotional hierarchy consisting of subcategories such as love, joy, anger, sadness, or fear. Furthermore, emotions are "often expressed physically (e.g., in gestures, posture, facial features); and may result in specific actions to affirm or cope with the emotion" (Bagozzi et al., 1999, p. 184). Thus, emotional contagion is concerned with the exchange of complex emotional packages through facial, vocal, gestural (Hatfield et al., 1994), or textual communication (Kramer et al., 2014).

Two research streams, namely primitive emotional contagion (Hatfield et al., 1994) and conscious emotional contagion (Salancik and Pfeffer, 1978), investigate emotional contagion from different angles. On the one hand, conscious emotional contagion incorporates the idea of people consciously adjusting their emotions to be appropriate to a certain situation (Salancik and Pfeffer, 1978). On the other hand, primitive emotional contagion, focusing on the exchange of emotional packages between two parties, treats emotional contagion as a largely unconscious human reaction (Salancik and Pfeffer, 1978; Gump and Kulik, 1997). Conscious emotional contagion is particularly present in ambiguous and stressful situations where people knowingly adjust their emotional expression (Salancik and Pfeffer, 1978; Gump and Kulik, 1997). Primitive emotional contagion, in contrast, focuses on the unconscious induction of emotions in everyday situations (Gump and Kulik, 1997; Kramer et al., 2014). Our hypotheses are based on the literature about primitive emotional contagion as (1) the situation of posting comments on newspaper articles does not fit to the definition of a stressful or ambiguous situation influencing the reader to adjust emotions consciously and (2) with primitive emotional contagion the reader mimics emotions unconsciously and thus reflects his or her actual emotional state.

Besides laboratory studies on emotional contagion (e.g., Hatfield et al., 1994; Dimberg, 1982; Hsee et al., 1990; McHugo et al., 1985), peer emotional contagion was studied through observational studies of offline social networks (Christakis and Fowler, 2007, 2008; Fowler and Christakis, 2008) and field experiments in online social networks (Kramer et al., 2014). Such studies of real-world networks on the influence of peers on an individual's emotional state (Fowler and Christakis, 2008), but also on subsequent actions (Christakis and Fowler, 2007, 2008), have the advantage of providing a more realistic setting and allowing for studying the dynamics of peer contagion. For example, the results of the Framingham Heart Study, in which an offline social network was observed over a time frame of 20 years, indicate that the probability of an individual being happy increases significantly if the person's direct peers are happy (Fowler and Christakis, 2008). Furthermore, the Framingham Heart Study demonstrated that an individual's emotional state cannot only be influenced by direct peers, but by peers with up to three degrees of separation (i.e., a friend's friend's friend). Similar peer influence was observed for the spread of obesity (Christakis and Fowler, 2007) and smoking (Christakis and Fowler, 2008).

Aral et al. (2009) questioned the causality of (emotional-) contagion effects by stressing that a separation between peer-to-peer influence and homophily is key. In more detail, homophily is the tendency of people in a social network to connect with similar others, for example, people with similar opinions and emotions towards particular topics (Aral et al., 2009), which potentially leads to highly correlating effects that not necessarily represent causal relationships. Addressing this issue, Kramer et al. (2014) conducted a week-long field experiment on Facebook to deeper analyse the causal relationship between experienced and subsequently expressed emotions in online social networks. In the experiment, which raised ethical concerns since no informed consent from participants was obtained (Flick, 2016), they changed the news feed of users (n = 689,003) partitioned into three groups. For one group the positive emotional content in the news feed was reduced, for the second group the negative emotional content was reduced, and a third group served as the control group without any changes. The results indicate that users exposed to positive emotions posted significantly more positive content. Vice versa, users exposed to negative emotions posted significantly more negative emotions.

Beyond emotional contagion effects, linguistic and non-linguistic biases are considered in our analysis, namely the positivity bias in the German (and English) language as well as the Pollyanna Hypothesis. First, the positivity bias is concerned with the bias of people to more frequently use adjectives that are connected to positive emotions than adjectives associated with negative emotions (Rozin et al., 2010). Second, the Pollyanna hypothesis describes the effect that individuals tend to memorize positive emotions easier than negative emotions (Boucher and Osgood, 1969). Accordingly, Boucher and Osgood (1969, p. 1) discovered the universal human tendency to use words associated with positive emotions "more frequently and divisively than evaluatively negative words".

3 Hypothesis development

Combining the above presented theoretical arguments and empirical findings on Emotional Contagion Theory suggests that positive or negative emotional stimuli of one individual can influence one or more other individuals' responses. These responses can either be similar or complementary (Hatfield et al., 1994). Regarding similar responses, Hatfield et al. (1994) give the example of a smiling person who influences its opponent to smile back. An example of complementary responses, also called counter-contagion, is a person raising a fist in anger, thereby causing the counterpart to shrink back in fear (Hatfield et al., 1994). Combining both mechanisms leads to our first hypothesis:

H1: The overall emotions expressed in online newspaper articles are positively associated with the overall emotions expressed in readers' comments.

Emotional Contagion Theory states that two major mechanisms account for primitive emotional contagion: (1) emotional mimicry / synchrony and (2) emotional experience and facial, vocal, and postural feedback (Hatfield et al., 1994).

First, mimicry, or synchrony, is given by an "observer acting as if in the other's place to the point of wincing at his pain, smiling at her delight or trying to avoid that person's danger" (Bavelas et al., 1987, p. 317). Early experiments carried out by Dimberg (1982) found evidence of mimicking by measuring facial electromyographic (EMG) patterns of participants facing each other in person. The Facebook experiment of Kramer et al. (2014) extended these findings to textually expressed emotions in online social networks. Hence, we hypothesize:

H2: The positive (negative) emotions expressed in online newspaper articles are positively associated with the positive (negative) emotions expressed in readers' comments.

Second, emotional experiences can actually change as a result of facial, vocal, and postural feedback, which leads to a "convergence of emotions among the interacts" (Hatfield et al., 1994). For example, if an individual in a social network increases the expression of negative emotions, the person's peers' emotional states will change to the negative and, in turn, they will show less positive emotions and vice versa. This cross-emotional encouragement effect goes beyond simple mimicry and synchronization, and it was shown to be present in Kramer's et al. (2014) field experiment on Facebook. We also expect to see a convergence of emotional states due to cross-emotional encouragement effects in online newspaper articles and readers' comments, which leads to our third hypothesis:

H3: The positive (negative) emotions expressed in online newspaper articles are negatively associated with the negative (positive) emotions expressed in readers' comments.

4 Data and methods

Our hypotheses lend themselves to quantitative, automated analysis of large data. Though human identification of emotions in text is still most accurate, it is less reproducible than computational methods and it is only feasible for a text corpus of quite limited size. Given the abundance of online articles and comments, automatic text mining techniques such as lexicon-based sentiment analysis are a viable option. In particular, since (lexicon-based) sentiment analysis has been carefully evaluated (Taboada et al. 2011) and it is commonly applied in similar contexts (Pennebaker and Graybeal, 2001; Ott et al., 2011; Golder and Macy, 2011; Kramer et al., 2014). Furthermore, a large variety of articles from different topics seems to be preferable in order to avoid selection biases and to make the hypothesis tests more reliable. For these reasons, we obtained data covering thousands of articles and comments from a major German newspaper on which we applied lexicon-based sentiment analysis.

4.1 Dataset

The dataset of our study stems from the online edition of "die Zeit" (see www.zeit.de), a major German national weekly newspaper with a reach of approximately 10 million unique visitors and 100 million page impressions per month. Some of the articles have an interactive in-text widget, consisting of a "yes or no" question related to the topic of the news article (e.g. Did chancellor Merkel act right in the refugee crisis?) and a mandatory free text field in which readers have to provide an argument for their answer. This widget was developed in collaboration between newspaper outlets such as Zeit Online and the start-up RAWR (see www.rawr.at). The same widget may be placed into multiple topically related articles in order to foster discussions over time and across articles. The "yes or no" answer and the comment of a reader are visible to all other readers after submission. In total, our unprocessed dataset including outliers consists of 29,935 comments associated with 1,159 news articles spanning a period of two years, starting from early 2015.

4.2 Sentiment analysis

As defined by Pang and Lee (2008), sentiment analysis is the automated classification of positive and negative opinions expressed in textual data, which is in line with the psychological definition of emotions to be either positive or negative (Hatfield et al., 1994). Broadly speaking, two computational approaches for sentiment analysis exist: machine learning and lexicon-based sentiment analysis (Chen et al., 2011). Algorithms that are based on machine learning learn the relationships between words and phrases appearing in a text, on the one hand, and the sentiments expressed in the overall text, on the other hand, through analysing example texts (i.e., training data). Algorithms that rely on lexicons compute sentiments by iterating over the words of a text and looking up the sentiment scores associated with each word in a predefined sentiment dictionary. Both approaches come with advantages and disadvantages. Even though sentiment analysis based on machine learning often outperforms lexicon-based approaches, the required training process involves expensive manual coding of examples of texts containing positive and negative emotions. Furthermore, machine learning models are highly dependent on the domain in which they have been trained and often fail to produce accurate results in other domains (Cambria et al., 2014). Lexicon-based approaches (Taboada et al. 2011), in contrast, do not require a training phase and can be used out-of-the-box, provided that an appropriate sentiment lexicon exists.

Due to a lack of manually labelled training examples, we chose to apply lexicon-based sentiment analysis to measure the emotions expressed in newspaper articles and associated readers' comments. We used the Linguistic Inquiry and Word Count (LIWC) dictionary developed by Pennebaker and colleagues (Pennebaker et al., 2001). LIWC has been used in studies of transcripts of everyday communication and press conferences (Pennebaker and Graybeal, 2001), online product reviews (Ott et al., 2011), tweets (Golder and Macy, 2011), as well as in the previously mentioned study on emotional contagion through Facebook posts (Kramer et al., 2014). LIWC consists of 2,300 words and word stems categorised among 68 different linguistic and psychological dimensions. The dimensions of LIWC consist of (1) standard language categories, (2) psychological processes, (3) relativity-related words, and (4) traditional content dimensions (Pennebaker et al., 2003). Especially important for the analysis of emotional contagion in online newspaper articles and readers' comments are the dimensions positive emotion and negative emotion (Pennebaker et al., 2003). Like the hierarchical view of emotions (Fischer et al., 1990), LIWC is also structured hierarchically (Pennebaker et al., 2003). For example, the word "cried" belongs to the categories "sadness", "negative emotion", "affect", and "past-tense verb", where sadness is a subcategory of negative emotion (Pennebaker et al., 2003; Fischer et al., 1990).

As our dataset consists of newspaper articles and readers' comments in German, we used the translated version of LIWC (Brand et al., 2003; Wolf et al., 2008). Interclass correlation (ICC) results indicate that the German version of LIWC and the original English version produce equivalent results, especially for the dimensions positive and negative emotions (Wolf et al., 2008). Furthermore, the German version of LIWC was tested for robustness against spelling mistakes (Wolf et al., 2008), which is useful for analysing readers' comments.

As newspaper articles and comments differ substantially both in length and emotionality, their sentiments scores need to be normalized in order to be comparable. We use a metric by Demers and Vega (2010) for testing H1. The overall emotions expressed per document corresponds to the total sentiment score tot_score_d per document (often called net-optimism). It is calculated by subtracting the number of words carrying negative emotions $w_{d,-}$ from the number of words carrying positive emotions $w_{d,+}$ and dividing the result by the total number of words present in a document:

$$tot\_score_d = \frac{w_{d,+} - w_{d,-}}{w_d}$$

The resulting normalized overall sentiment score can be interpreted as the net percentage of words in a document that are positive ($tot\_score_d > 0$) or negative ($tot\_score_d < 0$). Accordingly, emotions in this research study are treated as a continuous state ranging from very unhappy (-1) to very happy (+1) as opposed to the binary perception of happiness by, for example, Fowler and Christakis (2008). In order to test H2 and H3, we define the positive and negative sentiment scores of a document analogous to the above calculation as follows:

$$pos\_score_d = \frac{w_{d,+}}{w_d}$$

$$neg\_score_d = \frac{w_{d,-}}{w_d}$$

Even though the above calculations are common practice in sentiment analysis, one needs to consider that this definition of the sentiment score might not be optimal for short messages. For example, the two comments "good" and "This was a good game." differ by a factor of five in their total and positive sentiment scores. The first comment "good" obtains the maximal possible sentiment of one, since it is one positive word and the comment has only one word in total. Intuitively, it seems that the two statements should obtain a similar sentiment score. The problem is that short messages become very sensitive to the occurrence of a single emotional word. This is also in accordance to Figure 1, i.e. we found that only short comments convey extreme emotions, which may severely bias our results. One approach to address this concern is to use smoothing. For instance, additive smoothing is a common technique in the context of estimating the probability of a word (often within an n-gram). It assumes the existence of a word, even though it might not be observed in the data (Shen et al. 1999). In our context, we might assume that every comment contains a minimum number of neutral words by adding a small constant in the denominator. Such an approach limits the maximal absolute sentiment score of short messages severely, while allowing longer messages to have large sentiment scores. However, from a rational point of view there is no apparent reason, why a short message should not carry strong emotions. Therefore, we opted for another approach. We used conventional outlier analysis, where rare and extreme emotions are discarded that would otherwise strongly impact our regression analysis. Regression analysis is known to be sensitive to outliers due to using a squared error norm (Friedman et al., 2001). Removing outliers has to be done with great care. For our research question "Can emotions spread from online newspaper articles to readers' comments?" the focus is on determining whether this holds for the (vast) majority of people. A few people behaving in extreme ways should not change the result in a drastic manner. Therefore, outliers can be excluded.

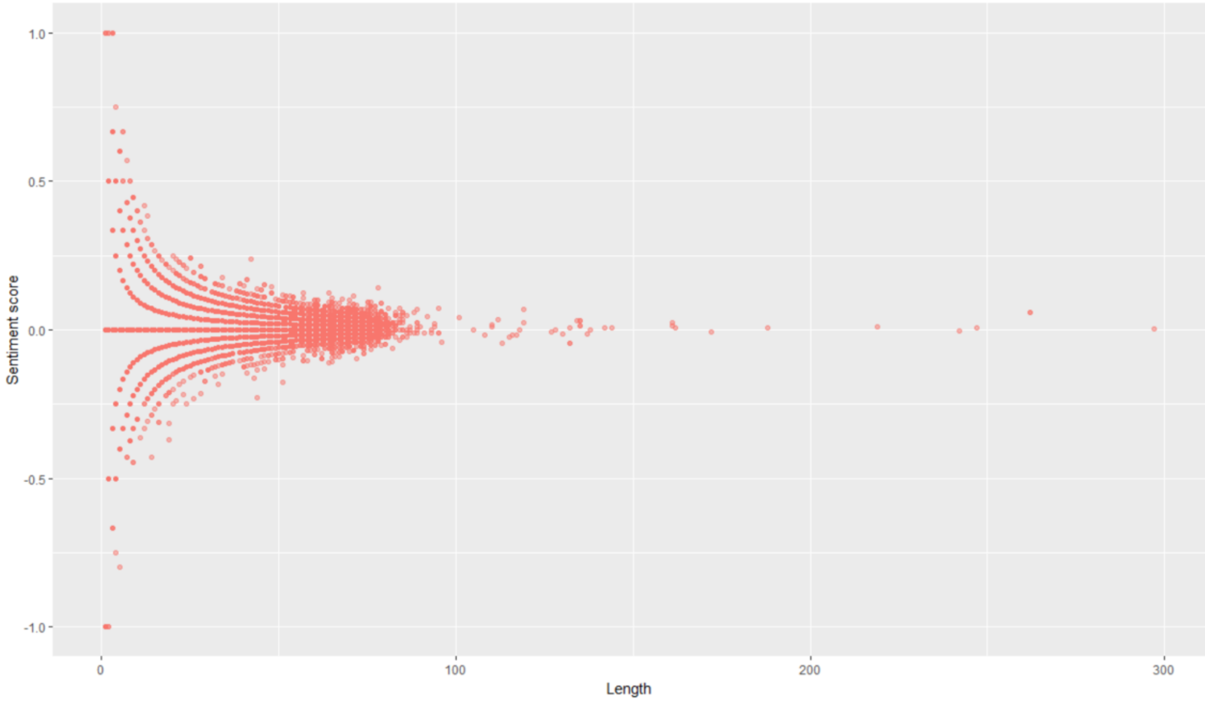

Figure 1 *Total sentiment scores as a function of comment length*

4.3 Multi-level regression models

To statistically test our hypotheses, we used multi-level linear regression models (Gelman and Hill, 2006), which are able to handle datasets that contain sub-groups of observations that are likely correlated. In our case, comments can be grouped by articles and users and it is to be expected that the sentiments of comments about a given article or from a given user are more highly correlated than the sentiments of comments that are not about the same article or from the same user. For example, we cannot rule out that the sentiments of comments, for example, for articles covering particularly emotional events like wars or natural disasters, are correlated. This within-group correlation violates the independence of observations assumption of Ordinary Least Squares (OLS) regression. Hence, we used multi-level models with random intercepts for articles and users into our models, which also reduces the risk of unobserved variables biases (e.g., users that are generally more positive or negative in their language).

Furthermore, to mitigate the risk of regression estimates being influenced by outliers, which is a common problem in linear regression models, we removed comments and articles with extreme sentiments. As indicated in Figure 1 and articulated in Section 4.2, extreme sentiments are a concern with short texts, i.e. comments. More precisely, comments which optimism score deviates by more than 3.3 standard deviations from the mean were omitted from the sample. This corresponds to including 99.9% of data for a normal distribution. For our data, this led to a reduction of 447 observations (or 1.5%). As shown in Figure 1, very strong sentiments occurred exclusively in comments, primarily very short comments, i.e. more than 95% of the removed comments contained at most 10 words.

5 Quantitative analysis

5.1 Descriptive statistics

Figure 2 presents density plots of the distribution of total sentiment scores in newspaper articles and readers' comments. The plot shows that both articles and comments exhibit a linguistic positivity bias, which is a well-known phenomenon in humans' use of natural language (Rozin et al., 2010). The bias is larger in magnitude for comments than for articles, i.e. the means are 0.0006 and 0.0001, respectively. A simple t-test confirmed that the bias for comments is significantly larger ($p<0.001$) and that both have a mean significantly different from zero ($p<0.001$).

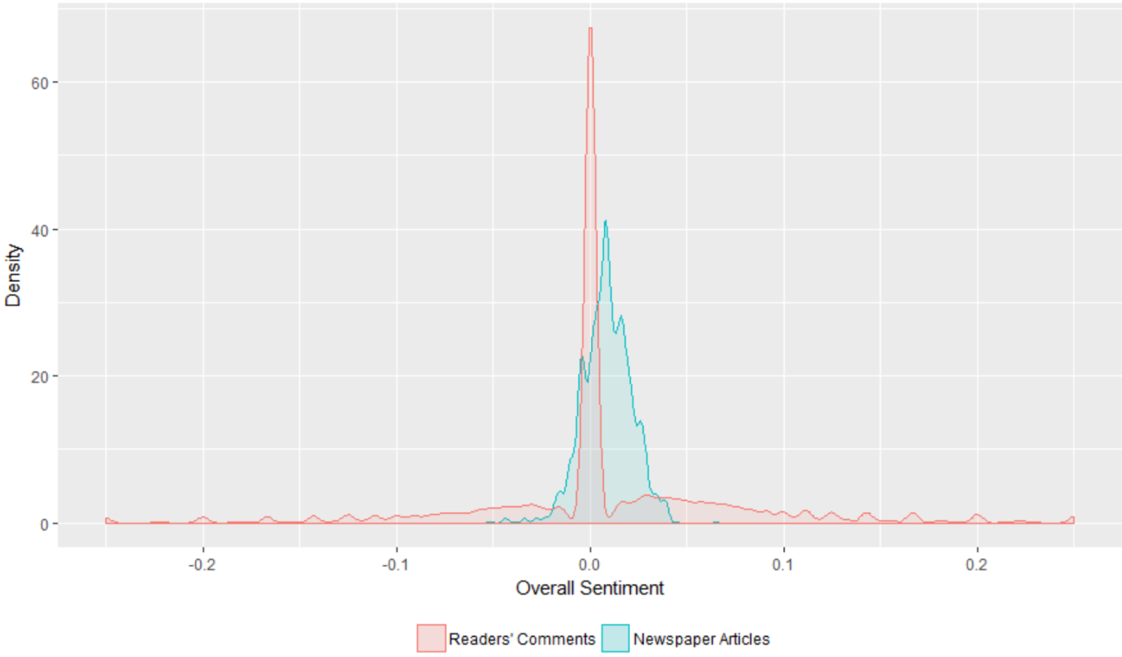

Figure 2 Sentiment scores for newspaper articles and readers' comments.

Figure 3 shows the distribution of aggregated overall sentiments of articles (top) and comments (bottom) over time. In more detail, each observation (i.e., article or comment) is plotted along the timeline (black dots). For each day, the sum of the sentiment scores of all observations is shown through coloured bars. Accordingly, Figure 3 indicates an increased adoption of the web 2.0 widget in online newspaper articles over time. However, no clear trend of sentiment scores relative to the time period is observable nor do the plots allow to discover correlation patterns between sentiment expressed in online newspaper articles and emotions stated in readers' comments. Thus, statistical tests of the previously outlined hypotheses are presented in the subsequent chapter.

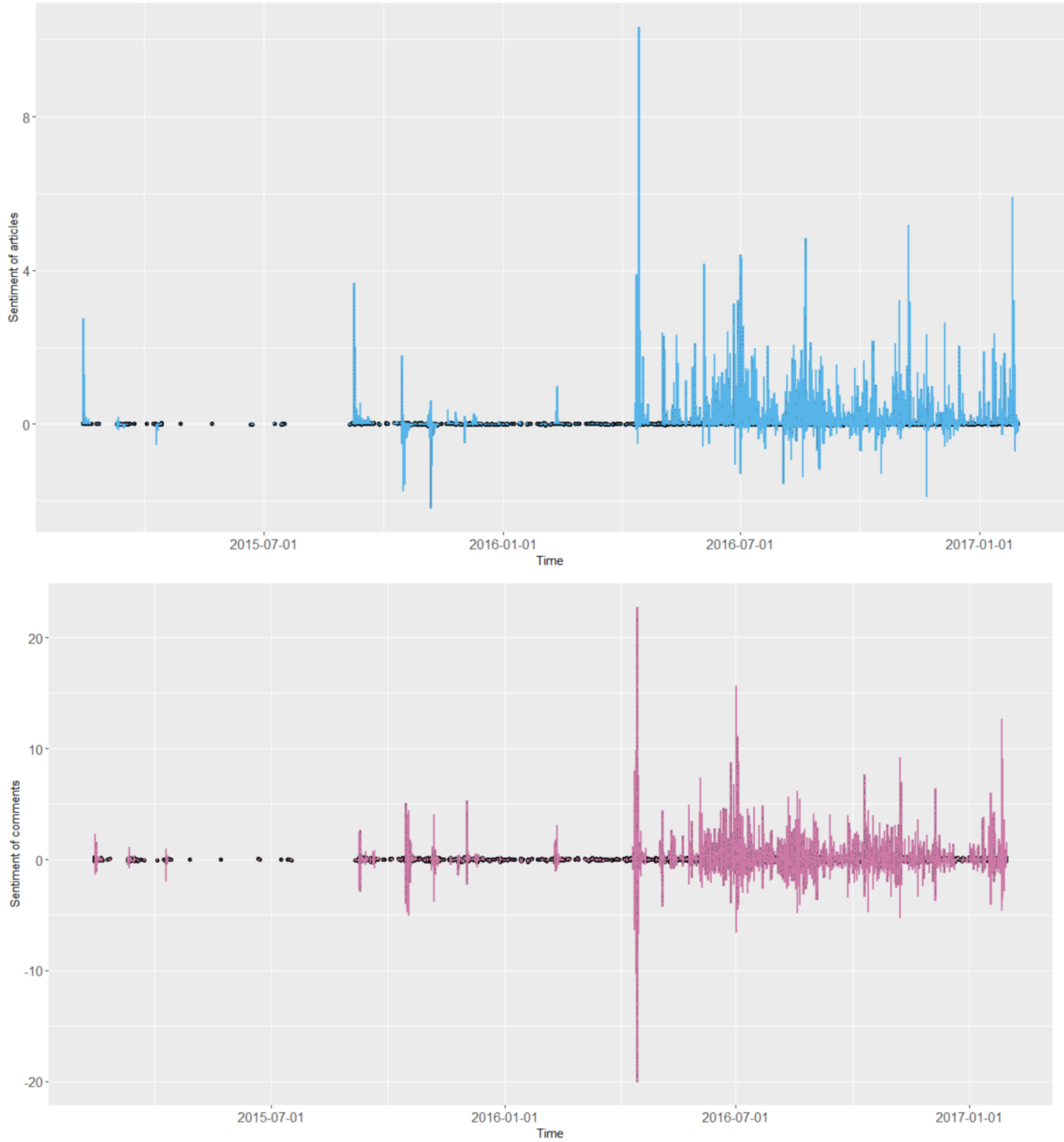

Figure 3 Sums of daily sentiments of articles (top) and comments (bottom)

5.2 Hypothesis tests

Table 1 provides an overview of our hypotheses tests. Furthermore, Table 2 presents the results of testing our first two hypotheses. Column 1 shows the coefficient estimates for H1, indicating that the overall sentiment of a newspaper article is significantly positively associated with the sentiment of readers' comments. A 10-percentage points change in overall article sentiment is associated with a change in the overall sentiment of comments of 2.8 percentage points. This result provides empirical evidence in support of H1. Columns 2 and 3 show the results of testing H2, which also provide empirical evidence in support of the hypothesis. A 10-percentage points change in positive sentiments expressed in a newspaper article is associated with a 4.3 percentage points change in the sentiment of readers' comments. The association between negative article sentiments and negative comment sentiments is also significant and positive, but substantially smaller in magnitude, i.e. a 10-percentage change in negative sentiments in an article results only in a 0.9 percentage points change in a comment.

Hypotheses	**Supported?**
H1: The overall emotions in articles are positively associated with overall emotions in readers' comments.	Yes, $p<0.001$
H2: The positive (negative) emotions in articles are positively associated with positive (negative) in readers' comments.	Yes, $p<0.001$ for positive and $p<0.05$ for negative emotions
H3: The positive (negative) emotions in articles are negatively associated with the negative (positive) emotions in readers' comments.	No

Table 1 Overview of hypotheses testing outcomes

	Dependent variable:		
	H1: Overall sentiment comment	H2: Positive sentiment comment	H2: Negative sentiment comment
	Confidence Estimates (95% Confidence Interval)		
Fixed Effects			
Intercept	0.0088***	0.0222***	0.0213***
	(0.0063 – 0.0096)	(0.0182 – 0.0251)	(0.0194 – 0.0232)
Overall sentiment article	0.2972***		
	(0.1930 – 0.3892)		
Positive sentiment article		0.43071***	
		(0.3179 – 0.5434)	
Negative sentiment article			0.089 *
			(0.0028 – 0.1773)
Random Effects			
Random intercept for articles	Yes	Yes	Yes
Random intercept for users	Yes	Yes	Yes
Observations	28,948	28,948	28,948
R^2	0.696	0.668	0.73

Notes: P-values calculated via Wald-statistics approximation.

*: $p<0.05$; **: $p<0.01$; ***$p<0.001$

Table 1 Multi-level regression models for testing H1 and H2

Table 2 shows the results of testing H3. The signs of the coefficients are as expected, but both coefficient estimates are non-significant, which means that there is no sufficient empirical evidence supporting the hypothesis.

	Dependent variable:	
	H3: Positive sentiment comment	H3: Negative sentiment comment
	Confidence Estimates (95% Confidence Interval)	
Fixed Effects		
Intercept	0.0353***	0.0240***
	(0.0316 – 0.0369)	(0.0215 – 0.0266)
Negative sentiment article	-0.0128	
	(-0.1287 – 0.1175)	
Positive sentiment article		-0.038
		(-0.1172 – 0.0491)
Random Effects		
Random intercept for articles	Yes	Yes
Random intercept for users	Yes	Yes
Observations	28,948	28,948
R^2	0.665	0.731

Notes: P-values calculated via Wald-statistics approximation.

*: p<0.05; **: p<0.01; ***p<0.001

Table 2 Multi-level regression models for testing H3

6 Discussion

Combining the theoretical ideas from Emotional Contagion Theory with our empirical results derived from the multi-level linear regression models provides insights into how emotions spread from online newspaper articles to readers' comments.

The significant positive estimate for the coefficient representing Hypothesis 1 indicates that a change in emotions expressed in newspaper articles leads to an analogous change in emotions expressed in readers' comments, which conforms with previous research (Hatfield et al., 1994; Kramer et al., 2014). When journalists express more positive emotions in their articles, readers will use more positive words in their comments as well. Vice versa, when journalists use more negative words, readers will also express more negative emotions in their comments. As the sentiment score in our study represents the percentages of words carrying positive (> 0) or negative (< 0) emotions per document, the coefficient estimate can also be interpreted as an increase in percentage points. For example, an increase of 10 percentage points in the sentiment score of online newspaper articles ceteris paribus is expected to result in an increase of 4.3 percentage points in readers' comments. While this effect may seem small at first sight, one should keep in mind that online newspapers have a large audience (10 million readers in our case). So, many small individual emotional contagion effects can lead to a large aggregated effect. Furthermore, readers that post positive or negative emotions online can also influence peers in other online and offline social networks, leading to even larger effects.

As outlined by Hatfield et al. (1994) and showed by Kramer et al. (2014), two major mechanisms account for the primitive emotional contagion process: (1) emotional mimicry / synchrony and (2) emotional experience and facial, vocal, and postural feedback. The results outlined in Table 1 relate to the emotional mimicry / synchrony mechanism (H2) and indicate that positive emotions in online newspaper articles positively influence positive emotions expressed in readers' comments. Likewise, negative emotions in online newspaper articles lead to an increase in negative emotions expressed in online newspaper articles. Together, these results support Hypothesis 2 and conform with the results of previous studies (Fowler and Christakis, 2008; Hatfield et al., 1994; Kramer et al., 2014). Interestingly, the coefficient estimate for the positive-to-positive contagion is four times larger in magnitude than the negative-to-negative effect. This suggests that it is much more difficult to infect an individual with negative emotions than with positive emotions.

The regression results reported in Table 2 relate to the emotional experience and facial, vocal, and postural feedback mechanism (H3), and do not provide sufficient evidence in support of this mechanism. Potential reasons could be one of the following: (1) the influence of non-linguistic cognitive processes (Boucher and Osgood, 1969), (2) the observation that cross-emotional effects are less strong (Kramer et al., 2014), (3) social distance to the source of influence (Fowler and Christakis, 2008), and (4) a not sufficiently large sample size (Kramer et al., 2014; Wooldridge, 2011).

As briefly mentioned earlier, our results also indicate that linguistic and non-linguistic biases are present. In more detail, indicators for a linguistic positivity bias and for the Pollyanna hypothesis are present in the analysed data sample (Boucher and Osgood, 1969; Dodds et al., 2015; Rozin et al., 2010). As outlined in Table 4, the positive-negative ratio is 1.4, both in newspaper articles (1.433) and in readers' comments (1.417), providing similar results to studies conducted on restaurant reviews (Jurafsky et al., 2014) and Google Books (Michel et al., 2011). However, linguists (Rozin et al., 2010) identified the strongest positivity bias in English compared to other languages including German, potentially explaining the difference in positive-negative ratios outlined in Table 4. Similarly, the Pollyanna hypothesis contributes to this ratio in favour of positive sentiment as people tend to remember positive emotions easier than negative emotions and thus express these more often (Boucher and Osgood, 1969).

Positive-negative ratio in readers' comments	Positive-negative ratio in newspaper articles	Positive-negative ratio in restaurant reviews	Positive-negative ratio in Google Books
1.4	1.4	2.7	1.8

Table 4. Positivity ratio in textual data. Positivity ratio of restaurant reviews based on Jurafsky et al. (2014) and Google Books based on Michel et al. (2011)

Consequently, the Pollyanna hypothesis, as well as the positivity bias, potentially influence the intercepts of the regression models outlined in our previous empirical analysis. Besides the Pollyanna hypotheses and the positivity bias in (German) language, homophily is another potential confounder reported to be present in networks of social ties. As introduced in Chapter 2, homophily is the tendency of people to connect with similar peers. Hence, homophily needs to be distinguished from contagious effects, which is particularly challenging for observational studies such as our study.

In addition, three important limitations need to be considered and provide potential ideas for further research. First, the textual data of this research study is exclusively in German. As previously outlined, languages bear characteristics such as the positivity bias that potentially influences the results. Furthermore, the LIWC was originally created for English textual data. Nevertheless, tests were performed analysing the consistency and reliability compared to the English version of the LIWC (Wolf et al., 2008), mitigating the risk of a dictionary bias in the results. Second, the effect of emotions is analysed for a single newspaper publisher. Accordingly, the results bear the risk of being influenced by the relationship between the publisher and the readers. As mentioned previously, it is necessary to differentiate between the influence of online newspaper articles on readers' comments and homophily. Homophily may lead to highly correlated outcome patterns due to shared opinions a priori to reading the article (Aral et al., 2009; Lazarsfeld and Merton, 1954). Moreover, the editorial policy of a newspaper publisher potentially influences what and how a newspaper publisher writes about topics. Also, the design of this research study does not allow inference on causal relationships between emotions used in online newspaper articles and emotions in readers' comments. In more detail, we meet Mill´s first criteria for causality "the cause has to precede the effect in time" (Gregor, 2006, p. 617) as users are restricted from posting comments before the newspaper article is published. Similarly we meet the second criteria "the cause and effect must be related" as we see correlation between the usage of emotions in online newspapers and readers' comments. However, we do not fulfil the third criteria "other explanations of the cause-effect relationship have to be eliminated" (Gregor, 2006, p. 617) because we can only control for specific users and articles (included random intercepts) on no other potentially influencing variables. Nevertheless, the results are consistent with experimental studies (Hatfield et al., 1994; Kramer et al., 2014) that identified a causal relationship between the exposure to emotion and experienced emotions. Third, extending the sample to other languages and online newspaper publishers could help to find significant results for emotional- and cross-emotional results by simultaneously mitigating the risk of a language bias (Jurafsky et al., 2014; Michel et al., 2011; Rozin et al., 2010; Boucher and Osgood, 1969) and homophily (Aral et al., 2009; Lazarsfeld and Merton, 1954).

7 Conclusions and further research

The emergence of the Web 2.0 allows users to share content and interact with each other, which can have the side-effect of emotions travelling through the Internet. In this study, we shed light on how emotions expressed in online newspaper articles influence emotions expressed by readers. We analysed 1,151 online newspaper articles with 28,948 associated readers' comments. By applying lexicon-based sentiment analysis and multi-level linear regression models, we modelled the relationships between sentiments in newspaper articles and comments. Overall, we find empirical evidence for the spreading of emotions from newspaper articles to readers' comments. Yet, we did not find evidence for all types of emotional contagion, which were earlier detected in studies of online social networks. In addition, our study provides insights into potential biases due to the positivity bias in human language and the Pollyanna hypothesis. Overall, our study contributes additional empirical evidence for emotional contagion through text-based interactions and, at the same time, extends prior research to environments which are less interactive than online social networks. Because emotional contagion through online newspaper articles potentially influences the emotional state of a large audience, this study has important implications for society as well as academia. Furthermore, besides affecting the well-being of people emotions are an important driver for opinion making and subsequent decisions about products and services, political parties, or behaviour such as eating and smoking. To further gain insights into how emotions spread in online environments, future studies should consider analysing emotional contagion in other contexts, for example, other languages, other cultures, or other communication channels. Additionally, studying the exchange of emotions through images and videos could help to better understand how emotions and subsequent opinions spread today and will spread in the future.

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