‘… A FRIEND INDEED?’ - AN EMPIRICAL ANALYSIS OF INTERACTIONS ON FACEBOOK

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Abstract

The rapid diffusion of online social networks has shifted a large proportion of human interaction away from traditional means of communication. The purpose of this work is to assess concerns regarding the quality of the relationships supported through online social networks. Properties of interaction are assumed to be a reasonable benchmark for the quality of relationships among people. Therefore, we analyze interactions on Facebook to examine how affective dimensions of messages determine the quantity and kind of interaction they experience. We find that (1) posting sad messages encourages peers to respond verbally, while (2) articulating positive emotions reduces verbal responses, but leads to more feedback in terms of received ‘likes.’ Text analysis shows that the sentiment of verbal responses is significantly determined by the sentiment of the message: (3) positive emotions trigger positive feedback, and (4) negative emotions trigger negative responses. We discuss implications of our findings with respect to contemporary theories of close relationships.

Keywords: Interactivity, Social networks, Computer-mediated communication.
1 Introduction

From its early days to the present, critics have articulated concerns about the social impact of the Internet as it could encourage people to spend more time alone, drawing them away from family and friends, thereby reducing interpersonal contact and interest in the local community (e.g., Kraut et al., 1998; Putnam, 2000). Meanwhile, scholars have argued that through its use for communication, the Internet could have important positive social effects on individuals (e.g., McKenna and Bargh, 2000; McKenna et al., 2002) and society at large (e.g., Hiltz and Turoff, 1978; Kraut et al., 2002).

Eventually, “whether the Internet will have positive or negative social impact […] may depend upon the quality of people's online relationships and upon what people give up to spend time online” (Kraut et al., 2002). Therefore, the present study deals with the quality of the relationships people maintain through online social networks.

Today, people use social networks to interact with each other at an unprecedented scope, altering the patterns in which people communicate worldwide. More time is spent on using social networks than on any other online activity such as search, email or instant messaging (Nielsen, 2010). Facebook is, by far, the largest social network with an active user base of more than 850 million people (Facebook, 2012). Therefore, a great deal of controversy in the media as well as in politics about people using social networks on the Internet is geared towards Facebook. This is why we address the issue of relationship quality in social networks by looking at interactions among people on Facebook.

Drawing on contemporary theories of close relationships, we argue that in order to assess the quality of people’s relationships, properties of interactions are a reasonable benchmark, particularly, affective dimensions of these interactions. Precisely, this work looks at emotional support through social networks by analyzing how affective dimensions of messages people post on Facebook determine the quantity and kind of interaction they experience. The findings are analyzed with respect to implications for relationship quality in social networks.

1.1 Communication “in the Stream”

Most communication in social networks follows a paradigm which is different from traditional media such as telephone or email (i.e., reciprocal), television or radio (i.e., one-way). On these platforms, people communicate “in the stream” (Zuckerberg, 2010) as they post brief messages without addressing a specific recipient. These messages (so-called “status updates”) are pushed into the “News Feeds” of all their friends who can decide to respond to them or not. In that, a Facebook friendship (or “following” someone on Twitter) is a subscription to someone’s messages broadcast, turning each user’s friend list into his or her individual communications audience.

Studies show that the way people communicate through social networks is well suited to support weak ties and access to novel information, i.e., bridging social capital (e.g., Ellison et al., 2007). The quality of the relationships people support through this channel can be questioned though, given that there is an upper limit on the extent to which people can earnestly maintain even superficial relationships (Gladwell, 2000; Donath and Boyd, 2004; Schöndienst and Dang-Xuan, 2011). Recent studies have contributed to the notion of Facebook being a place to engage in superficial relationships while avoiding genuine friendship and empathy (e.g., Buffardi, 2008; Mehdizadeh, 2010).

In contrast to this perception, various studies have found a positive relationship between intensity of Facebook use and bonding social capital which is derived from close relationships and is taking the form of emotional or tangible support (Ellison et al., 2007; Steinfield et al., 2008). However, it is important to note that Facebook started out as a social network for students to connect to their classmates. It is only since late 2006 that Facebook opened up to users outside this closed community and, since then, has increased their user base from 40 to more than 850 million (Facebook, 2012).
Therefore, one may expect that “changes to the structure of the site, and the associated interactions enabled by those changes, may have altered the types of relationships people support through Facebook” (Vitak et al., 2011; p. 6). In fact, a recent study contradicts the findings from earlier research as it could not find a relationship between Facebook use and the formation of bonding social capital (Vitak et al., 2011). Stream communication has quickly become an essential part for many people’s daily communication activities. Given that, today, a significant amount of people’s interactions take place by means of stream communication, it is important to analyze the social aspects of this form of communication.

1.2 Properties of Interaction and Relationship Quality

Starzyk et al. (2006) argue that for “appraising one’s acquaintance with any person” (p. 1) “the quantity of interaction matters, but so does the quality” (p. 13). Indeed, the level and quality of interaction facilitated “in the stream” can serve as an important benchmark for the quality of the relationships supported through social networks, and, ultimately, for the value they create for its users. Interaction is an exchange between people, and, on Facebook, users interact largely “in the stream” by posting messages, commenting on other people’s messages, or simply ‘liking’ them. Burke et al. (2010) provide evidence that, among others, greater feelings of bonding social capital and lower loneliness are associated with higher amounts of ‘likes’ and comments people receive upon their messages. Therefore, the level of experienced interaction appears to be an important indicator for the quality of relationships people maintain “in the stream” and, consequently, the value they derive from using the platform.

Reciprocity is an important factor in defining relationship strength and maintenance (Granovetter, 1973; Putnam, 2000). Receiving no feedback upon messages may indicate a poor level of quality regarding the relationships maintained on the platform. Meanwhile, the act of (a) ‘liking’ and the act of (b) commenting on messages imply different qualities of feedback. ‘Liking’ is a swift way to respond to a message, which requires no codification effort and little cognitive or emotional involvement. It is therefore more of a signal than a profound response. Commenting, on the other hand, requires people to deal with the content of a message, implying both codification and cognitive effort to articulate the verbal response. In contemporary theories of close relationships, emotional support is of central importance (e.g., Cunningham and Barbee, 2000; Reis, 2001). Wellman and Wortley (1990) show that “the strength of a relationship has the strongest association of all variables with emotional support” (p. 566). Scholars have conceptualized the emotional support construct around various reactions to people who are in “times of stress or upset” (Burleson, 2003; p. 2). These reactions may include care, concern, love, and interest (Cutrona and Russell, 1990). In order to assess emotional support on Facebook, it is relevant to understand how the sentiment articulated in a message influences both the quantity and affective dimensions of the feedback it triggers. Particularly, the responses to those messages in “times of stress or upset” may point towards the depth of the relationships maintained in the social network. As discussed, feedback in terms of ‘likes’ and comments imply a qualitative difference. Further, though, the affective dimensions of a comment may be just as relevant for an assessment of the relationships maintained “in the stream.” Therefore, in this paper, we address the following research question:

RQ: How do affective dimensions of a message determine (1) the quantity as well as (2) the sentiment of the feedback it triggers?

To this end, we proceed as follows. In the following section, we review related work and derive our hypotheses. Next, we employ text analysis and regression analysis to test our hypotheses using a data set of 8,192 messages and 15,728 corresponding comments. Finally, we conclude with a discussion of our results with regard to implications for relationship quality in social networks.
2 Theoretical Foundation and Model

2.1 Messages’ Affective Dimensions

As discussed above, emotional support is a crucial component of sincere relationships, particularly at “times of stress or upset” (Burleson, 2003; p. 2). The importance of properties of emotionality and their effects has been investigated by scholars from various disciplines. In general, “affect appears to influence what we notice, what we learn, what we remember, and ultimately the kinds of judgments and decisions we make” (Forgas, 2006; p. 273). In stream communication, an individual makes a decision whether to ignore someone’s message or to respond to it by ‘liking’ or commenting on it. This section reviews related literature on how emotional properties of a message may influence this decision and derives hypotheses on the effect of a message’s affective dimensions on feedback.

Analyzing how people talk and write provides a window into their emotional and cognitive worlds (Pennebaker et al., 2006). Scholars have shown that the words people use correlates with their physical and mental health (e.g., Gottschalk and Glaser, 1969; Stiles, 1992). If there was a lack of empathy in relationships on Facebook as suggested by scholars (e.g., Mehdizadeh, 2010) one should expect interaction to follow a “rich get richer, poor get poorer” dynamic, i.e., people who do well and share messages with a positive sentiment would receive more feedback, while the ones articulating negative emotions would be avoided and get less feedback. An example of such a dynamic is reported by Coyne (1976) who suggests that depressed women constantly report depressive symptoms, which would ultimately leads to social rejection and a further worsening of their condition.

On the other hand, results from a study of online interactions (Joyce and Kraut, 2006) suggests that negative affect of messages can actually trigger participation. This, however, seems to apply to negative affect in terms of anger rather than sadness or fear. Meanwhile, the same study finds that positive affect in messages encourages continued participation in newsgroups by creating a sense of community among users. These results were confirmed in a large-scale study of online communities (Huffaker, 2010) showing that people who use affective language in their messages receive more feedback than those who do not. This applies to both positive and negative emotions. Further, Smith and Petty (1996) show that positive as well as negative framing of a message can create attention and cognitive involvement, in particular when the framing is unexpected for the recipient of the message.

As the findings of the positive effect of positive emotions in messages are consistent throughout the literature, we hypothesize:

\[ H1: \text{The more positive emotions a message contains, (a) the more ‘likes’ it receives, and (b) the more distinct comments it triggers}. \]

The findings on the effect of negative emotions are mixed. ‘Liking’ a message implies endorsing or praising which we do not associate with negative emotions, unless in a gloating or sarcastic manner. ‘Likes’ may therefore be negatively related to messages articulating negative emotions. Meanwhile, findings on verbal responses to negative emotions have been mixed. Overall though, studies suggest that the use of Facebook can be associated with psychological well-being (Ellison et al., 2007; Steinfield et al., 2008; Burke et al., 2010). Therefore, we expect messages with a negative sentiment to actually encourage peers to respond rather than to react with withdrawal. Therefore, we hypothesize:

\[ H2: \text{The more negative emotions a message contains, (a) the less ‘likes’ it receives, and (b) the more distinct comments it triggers}. \]

2.2 Affective Dimensions of Feedback

In order to assess relationship quality, it deepens the analysis to depart from solely looking at factors which determine the quantity of feedback. So far, we distinguished between feedback in terms of ‘likes’ and feedback in terms of comments. While ‘likes’ have an inherently positive sentiment verbal
responses can articulate either positive or negative affect. At this point, we will therefore investigate the affective dimensions of the verbal responses, i.e., the comments which messages receive.

There is reason to expect that the affect articulated in a message will be picked up by the subsequent verbal responses. It is known that in verbal interaction communication partners sync their wording which would indicate that messages which contain positive (negative) emotions words are likely to receive verbal responses which also express positive (negative) emotions. Further, Huffaker (2010) provides evidence for the concept of language diffusion in online communities as the more often people used words that express affect the more of the words they used were repeated in the subsequent replies. Human populations are arranged in social networks that determine interactions and influence not only the spread of behaviors and ideas, but also emotions. Hill et al. (2010) show that, over long periods of time, emotional states spread in the same way as do contagious diseases across social networks. In various contexts, it has been shown that both positive and negative moods can be “infectious,” for example during workplace interactions (Barsade, 2002) or in negotiations (van Kleef et al., 2004). The findings from both studies on contagion of emotional states, as well studies on language diffusion (e.g., Huffaker, 2010) suggest that the sentiment of a message would trigger verbal responses of the similar sentiment. Therefore, it is hypothesized that:

**H3:** Messages which articulate positive emotions, trigger feedback with positive emotions.

**H4:** Messages which articulate negative emotions, trigger feedback with negative emotions.

![Research Model](image)

*Figure 1. Research Model*

Based on the literature, we could derive hypotheses regarding the interplay of positive emotions and negative emotions. Figure 1 summarizes our research model. In addition, we will post-hoc investigate exploratory distinct dimensions of these categories (i.e., subcategories) such as positive feelings, optimism, anxiety, anger and sadness.

## 3 Methodology

### 3.1 Data Collection

In order to analyze interaction on Facebook, we obtained the messages which users posted on their Wall and the corresponding feedback they received upon them in terms of ‘likes’ and comments. People’s messages and profile information are usually not publicly available on Facebook and can only be accessed by friends. Therefore, 20 seed users were recruited to manually save the profile page and messages including all feedback of about 30 randomly selected friends (of course, each with permission) as HTML files. A Facebook user’s Wall shows all messages he or she posted including the corresponding conversations (in terms of the subsequent comments) and ‘likes’ from all his or her friends. We then provided a Java-based script to parse and anonymize the data and convert them into a
CSV file. To ensure different levels of income and education and, thus, diverse social networks, seed users were recruited from diverse backgrounds (9 nationalities, 10 professions). The average age of the seed users was 24, spanning from 17 to 45. The seed users were divided into two groups, each consisting of 10 people, with an equally balanced male-female ratio. Both groups crawled data over an eight-week period (June 21 - August 15, 2010, and August 16 - October 1, 2010, respectively).

We obtained profile information and messages including all corresponding feedback of 501 users in total. Some users do not explicitly state their gender or age on their profile page. In these cases, the gender was guessed from the name. However, this procedure did not allow us to collect information about users’ date of birth, which prevents us to include effects of people’s age in our analysis. The social networks of the seed users had no overlaps so that no profile was crawled twice. In total, 13,667 Wall posts were obtained including the 26,240 corresponding comments. About 40% of the messages featured uploaded photos, automatically generated messages from Facebook games (e.g., “Farmville”), or other applications which are beyond the scope of this study and, therefore, excluded from the analysis. 56 users who had Wall posts only of such kind were excluded. This yielded a data set comprising messages from 455 users including corresponding likes and comments.

3.2 Variables and Analysis Methods

We used the Linguistic Inquiry and Word Count (LIWC) Software (Pennebaker et al., 2006) to determine the affective dimensions (i.e., positive and negative emotions) of messages as well as of corresponding verbal responses. LIWC is a text-analysis software program that places words from a text file into categories based on a series of built-in dictionaries. These dictionaries have over 4,500 words and word stems containing a total of 80 categories into which words may fit. LIWC has been widely used for academic purposes in psychology, linguistics and other social sciences.

In our study, we used the LIWC categories “positive emotions” and “negative emotions” to profile sentiment articulated in messages and corresponding comments. While “positive emotions” contains sub-categories such as “positive feelings” and “optimism,” “negative emotions” is, among others, related to the sub-categories “anxiety,” “anger” and “sadness.” These (sub-)categories were created using emotion rating scales and thesauruses and validated by independent judges.

As our analysis deals with postings on Facebook, where the use of short forms, acronyms and emoticons is not unusual, we performed the following steps to additionally ensure the validity of the measurement of sentiment. First, we added to the LIWC standard dictionaries a custom list of short forms and acronyms that might indicate sentiment as well as another list of emoticons. Second, we addressed the issue of potential ambiguity in case that a message might contain both positive- and negative-emotion words. Also, there is another problem related to the negation of adjectives (e.g., “I am not that happy!”). In such cases, two independent coders were employed to manually identify the overall sentiment. Inter-coder reliability constituted 0.95 (p < 0.00) suggesting a high level of agreement between the coders (Landis and Koch, 1977). However, there still might be real mixed-emotional posts, i.e., posts that contain both positive and negative content. For example, a message of that nature might be like this: “I love helping people out but hate spending money.” We decided to drop such mixed-emotional posts in order to avoid any potential ambiguity.

Due to the fact that our seed users have different nationalities, the languages used in the messages and comments of their friends were diverse. Therefore, we manually classified all messages and corresponding verbal responses by language and obtained a distribution indicating English as the most used language (45%), followed by German (35%). Other languages (20%) included Chinese, Vietnamese, Russian, and Bulgarian which are not covered by current LIWC dictionaries. The analysis of affective dimensions is, therefore, limited to a subsample consisting of 6,554 English or German messages and the corresponding verbal responses.

To test our hypotheses, we constructed the following variables with regard to each message:

- number of ‘likes’ (LIKES)
• number of distinct comments (i.e., from different persons) (COMMENTS)
• word count (MSGWORDCOUNT)
• number of words indicating positive emotions (MSGPOSEMO) and negative emotions (MSGNEGEMO)

Accordingly, we calculated the number of words indicating each subcategory of positive and negative emotions, respectively:
• positive feelings (MSGPOSFEEL), optimism (MSGOPTIM)
• anxiety (MSGANX), anger (MSGANGER) and sadness (MSGSAD)

Likewise, we introduced LIWC measures of affective dimensions with regard to corresponding verbal responses (i.e., comments) to each message. Since each message can trigger multiple verbal responses, we calculated the average numbers of LIWC words for each category over all comments. Note that since about 18% of the messages did not get any responses (i.e., no comments to be processed by LIWC at all), the subsample is reduced to 5,244 messages. The resulting variables are:
• average word count of all corresponding comments (COMWORDCOUNT)
• average number of words indicating positive emotions (COMPOSEMO) and negative emotions (COMNEGEMO) in the comments

Accordingly, we calculated the average number of words indicating each of the following subcategories:
• average number of words indicating positive feelings (COMPOSFEEL) and optimism (COMOPTIM)
• average number of words indicating anxiety (COMANX), anger (COMANGER), and sadness (COMSAD)

In addition, we included user’s number of Facebook friends as well as posting frequency as control variables in our model. Studies suggest that there is an inverted U-shape relationship between a Facebook user’s friend count and received feedback as well as social capital (e.g., Schöndienst and Dang-Xuan, 2011; Ellison et al., 2011). Regarding posting frequency, studies show that user’s posting frequency has also an impact on received feedback (e.g., Mehdizadeh, 2010) and the feeling of connectedness (e.g., Köbler et al., 2010). Finally, we included a gender dummy to control for possible gender differences:
• number of friends the user has (FRIENDCOUNT)
• frequency (per week) at which the user posted pure-text messages (FREQUENCY)
• gender (SEX)

Regarding H1 and H2, the dependent variables representing the quantity of feedback (LIKES and COMMENTS) are true event count data, i.e., they are non-negative and integer-based. Therefore, we apply Poisson regression model (Cameron and Trivedi, 1998). Poisson regression relies on a log-transformation of the conditional expectation of the dependent variable and requires an exponential transformation of the coefficients for assessing and interpreting their effect sizes. The resulting regression models are as follows:

\[ \log(E(\text{LIKES})) = \beta_0 + \beta_1 X + \beta_2 \text{MSGWORDCOUNT} + \beta_3 \text{FRIENDCOUNT} + \beta_4 \text{FREQUENCY} \]
\[ + \beta_5 \text{SEX} + \alpha_i + \epsilon \]

\[ \log(E(\text{COMMENTS})) = \beta_0 + \beta_1 X + \beta_2 \text{MSGWORDCOUNT} + \beta_3 \text{FRIENDCOUNT} \]
\[ + \beta_4 \text{FREQUENCY} + \beta_5 \text{SEX} + \alpha_i + \epsilon, \]

where \( E(\text{LIKES}) \) and \( E(\text{COMMENTS}) \) are the conditional expectation of LIKES and COMMENTS, respectively. \( X \) denotes each of the sentiment-related variables regarding messages such as MSGPOSEMO, MSGNEGEMO as well as MSGPOSFEEL, MSGOPTIM, MSGANX, MSGANGER, and MSGSAD. \( \alpha_i \) represents the unobservable individual fixed-effect of each person (i.e., user) denoted by the index \( i \) (Baltagi, 2008).
In H3 and H4, we expect that the more words indicating (a) positive and (b) negative emotions, respectively, a message contains, the more positive-emotions and negative-emotions words, respectively, will also occur in subsequent comments. Since the dependent variables COMPOSEMO and COMNEGEMO are average quantities of words indicating sentiment occurring in corresponding comments and thus not true count data, we applied regression analysis using Ordinary Least Square (OLS) estimation to test H3 and H4. To account for the possibility that the dependent variables are not normally distributed, we log-transformed the dependent variables before employing OLS regression. The regression model is as follows:

\[(3) \log(Y) = \beta_0 + \beta_1 X + \beta_2 MSGWORDCOUNT + \beta_3 FRIENDCOUNT + \beta_4 FREQUENCY + \beta_5 SEX + \alpha_i + \epsilon,\]

where Y denotes each of the sentiment-related variables regarding verbal responses (i.e., comments) such as COMPOSEMO, COMNEGEMO as well as COMPOSFEEL, COMOPTIM, COMANX, COMANGER and COMSAD. Otherwise, the right-hand side of the equation is identical to (1) and (2).

### 4 Empirical Results

In our sample, the mean (median) values of (a) ‘likes’ or (b) comments a user receives are (a) 1.53 (1.20) and (b) 1.92 (1.79), respectively. About 18% of the messages did not get any kind of feedback at all. Users of our sample (235 female, 220 male) have an average (median) number of 305 (235) friends. On average, users in the sample post more than two messages per week (2.25).

#### 4.1 Messages’ Affective Dimensions

The regression results in Table 1 show that messages which feature more words associated with positive emotions tend to trigger more feedback in terms of ‘likes’, which supports H1a. The coefficient of MSGPOSEMO is significantly positive \((b = 0.04, p < 0.001, \text{see Model (1)})\). This also holds for the subcategories positive feelings or optimism. However, against our expectation, the number of people who respond verbally decreases in the number of positive emotion words implying no support for H1b as the coefficient of MSGPOSEMO is significantly negative \((b = -0.08, p < 0.001, \text{see Model (2)})\). Likewise, MSGPOSFEEL and MSGOPTIM are negatively associated with COMMENTS. Results for the effect of negative emotions word in messages are vice-versa. Messages containing more words indicating negative emotion lead to less ‘likes’ (H2a supported) and more verbal responses (H2b supported). Both coefficients of MSGNEGEMO in Model (1) and (2) are highly significant \((b = -0.13, p < 0.001, \text{see Model (1)}; b = 0.08; p < 0.001, \text{see Model (2)})\).

As Poisson regression was applied, the interpretation of the estimated coefficients requires an antilog (i.e., exponential) transformation of the coefficients. For example, the coefficient of MSGNEGEMO in Model (1) is -0.13 meaning that a one-unit change in the number of negative-emotion words, on average, will trigger 13% less ‘likes’ \((\exp(-0.13) = 0.87)\) while in Model (2), MSGNEGEMO has a coefficient of 0.08 meaning that a one-unit change in the number of negative-emotion words, on average, will trigger 8% more comments \((\exp(0.08) = 1.08)\).

In addition, among subcategories of negative emotions, sadness (MSGSAD) also exerts a similar significant effect on LIKES and COMMENTS. With regard to control variables, word count has a significant impact on both ‘likes’ and verbal responses throughout all regression specifications, while other variables do not have any significant effect at all, except FREQUENCY with respect to LIKES.
### 4.2 Affective Dimensions of Feedback

**H3 is not supported** by our results as shown in Table 2 as the use of positive-emotion words does not exert a significant increase in the use of equivalent words in subsequent verbal responses. The coefficient of MSGPOSEMO is insignificant. However, by looking at the subcategories of positive emotions, we find significant positive relationships between MSGPOSEFEEL and COMPOSEFEEL ($b = 0.22, p < 0.001$) as well as MSGOPTIM and COMOPTIM ($b = 0.30, p < 0.001$). On the other hand, our results suggest that messages which articulate negative emotions tend to trigger verbal responses that use negative emotions words as well ($b = 0.33, p < 0.001$). This provides support for **H4**. Among the subcategories of negative emotions, MSGANGER is also significantly positively related to COMANGER ($b = 0.53, p < 0.001$). Further, all control variables do not have a significant impact on the dependent variables, except word count.

### 5 Discussion

The purpose of this work is to assess concerns regarding the quality of the relationships people support through social networks. We described how people interact “in the stream” and how that differs from communicating through traditional communication channels. We presented literature which links properties of interaction between people to the quality of their relationship. With respect to this literature, our findings on interactions on Facebook allow for some conclusions on the quality of relationships people maintain in social networks.

Regarding the first part of our research question, our results reveal that a message which articulates positive emotions decreases the amount of people who respond verbally. This is unexpected because studies suggest that positive sentiment of a message actually encourages others to respond (e.g., Johnson, 2009; Huffaker, 2010). Since messages which articulate a positive sentiment receive significantly more ‘likes’ though, it appears that people opt to simply ‘like’ those posts, rather than making the effort to codify a verbal response. In that sense, ‘likes’ absorb comments in response to messages which articulate a positive sentiment. Contemporary theories of close relationships find emotional support to be one of the most important qualities (e.g., Reis, 2001).
The purpose of this work was to assess concerns regarding the quality of the relationships people support through social networks. More specifically, we assess emotional support as a benchmark for relationship quality by examining how affective dimensions of messages people post on Facebook determine the quantity and kind of interaction they experience on the platform. Indeed, we find that...
sentiment articulated in a message significantly determines the quantity as well as the sentiment of the feedback it triggers.

This shows that the feedback people receive upon messages is neither random, nor does it solely depend on the information provided. Rather, our findings indicate that interactions in the world’s largest and most widely used social network, Facebook, fulfil crucial components associated with close relationships: people can turn to their Facebook friends with sad messages and expect to receive verbal responses. This speaks for the quality of the relationships people maintain through Facebook and shows that social networks can facilitate valuable exchanges among people.

However, it is a limitation of our study that our findings apply only to the interactions among Facebook’s 850 million users. In future studies, we will include other classes of social networks as platform design features may greatly influence users’ behaviour. The dynamics of interaction may differ in smaller, more intimate social networks such as communities of interest. Other social networks allow for different kind of interactions, which may have different implications for the quality of the relationships maintained through these networks. While computerized language measures allowed us to test our hypotheses on a large data set, they could not capture context, irony, sarcasm, and idioms. As future work, we aim at backing up our findings by conducting additional qualitative analyses.

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