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# Change in Humor Styles on Twitter During Development of Ebola Crisis

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Abstract

An ongoing trend in the field of crisis communications is the increased presence of humorous tweets during crises. The current study aims to contribute to the knowledge about this trend by analyzing which types of humor are more common at what moment in the crisis' development, are more prevalent in which content categories and are more often used by which types of users. This was done by evaluating 10.000 tweets – selected from a larger corpus containing tweets about the Ebola crisis – on type of humor, content type and user type. Findings showed that the amount of humorous tweets peaked about half a year after the start of the crisis. Moreover, governmental organizations and civilians were found to use the highest amount of humor. Also, humor was present the most in tweets containing first hand reporting and in tweets criticizing the government. The outcomes for specific types of humor were highly diverse. The findings of this study are especially useful for those organizations and institutions who wish to actively take part in the online discussion during crises. They can use these outcomes in adapting their social media content strategies.

*Keywords:* crisis communications, Ebola, humor, social media, Twitter

In November 2015, terrorists attacked Paris, killing 130 people and leaving many wounded (BBC, 2015, December 9). Within hours, people from all over the world were posting Tweets using the hashtag #PrayersForParis (Twittereurope, 2016). Earlier that year, the hashtag #BlackLivesMatter arose as a reaction to the shooting incidents in Ferguson, Charleston and Baltimore involving the American police and Black citizens (Valasek, 2015). The hashtag was used more than 9 million times.

It is clear that Twitter, “a free social networking and micro-blogging service” (Signorini, Segre, & Polgreen, 2011, p. 1), has started to play a big role in crises. However, the contributions to these online discussions are not only serious. Another remarkable trend is the increasing presence of humor in tweets during crises (Chew & Eysenbach, 2010; Mollema, et al., 2015). During the H1N1 outbreak in 2009, for example, a Twitter user tweeted “Rupert Grint had Swine Flu. It’s VOLDEMORTS COMEBACK!” (Chew & Eysenbach, 2010, p. 3). At almost every stage of this outbreak, humor was the most dominant sentiment, present in 10 to 22% of the total amount of tweets.

This research will continue exploring the presence of humorous tweets during crises, and the Ebola crisis in particular. The decision for the Ebola crisis is based on the fact that many previous studies on the role of Twitter during crises are related to diseases or viruses (Chew & Eysenbach, 2010; Mollema, et al., 2015; Signorini, Segre, & Polgreen, 2011). Using a new crisis within the same crisis category to explore the relation between humor and crises will give an interesting addition to previous research.

Moreover, this research will give a more in depth analysis of the relation between humor and crises by looking into more specific types of humor as well as into types of content and users on social media. Finally, this research will look at the development of these variables over the development of the crisis, uniting research done on time and humor (Chew & Eysenbach, 2010; McGraw, Williams, & Warren, 2014; Spence, Lachlan, Lin, & Del Greco, 2015) and on humor and crises (Chew & Eysenbach, 2010; Mollema, et al., 2015).

The outcomes of this study could be useful for organizations, such as the World Health Organization (WHO), news outlets or governments, that wish to participate in the conversation on Twitter during (health) crises. This study will help create an image of which users take part in this conversation, what topics they wish to talk about at what point in time, and when they use – and therefore possibly expect others to use – which types of humor. With all this information, those organizations, news outlets and governments can adapt the content of their tweets, and find out if Twitter is a useful platform to reach their target groups with the information they want to spread.

## Literature review

**Types of humor.** Humor is a broad concept, entailing many different types, such as irony and wordplay. Martin, Puhlik-Doris, Larsen, Gray and Weir (2003) offered a categorization of humor based on its offensiveness. They identified four styles: affiliative, self-enhancing, aggressive and self-defeating. The first two belong to the group of 'adaptive' or positive humor styles. Affiliative humor is meant to improve the relationship with another in everyday situations, while self-enhancing humor focuses on overcoming stressful situations. The second two styles are considered to be 'maladaptive' or negative humor styles. Aggressive humor involves jokes or remarks that can be hurtful to others, while self-defeating humor means that someone is making himself the subject of the jokes as, for example, a defense mechanism.

Instead of a categorization based on offensiveness, humor can also be classified based on content. Hay (1995) made such a categorization, identifying the following types of humor: anecdote, fantasy, insult, irony, joke, observational, quote, roleplay, self-deprecation, vulgarity and wordplay. These categories seem to be more extensive, clear and easy to identify than those of Martin et al. (203).

Even though studies like these two on the categorization of humor is widespread, none seem to have looked into the use of specific types of humor on social media, let alone during crises. This research will therefore take the above-mentioned categorization of Hay (1995) into account, and look at their usage on Twitter during the Ebola crisis. The humor categories will also be compared with different types of content and users. The goal is to find out whether certain types of humor are more common in certain types of content or used more often by certain types of users.

**Types of content.** One main step in further discovering the use of humor on Twitter, is analyzing which types of content are more likely to contain humor. The types of content on Twitter also reflect what the social media platform is used for, which is an important variable to analyze according to the *uses and gratifications theory*. This theory emphasizes what people do with (social) media, instead of looking at what media do to people (Katz, 1995). The latter has been dominating research within the field of mass communications as well as crisis communications for a long time, while many studies have shown the relevance and the importance of applying a uses and gratifications approach (Chen, 2011; Houston, et al., 2014; Katz, 1995; Whiting & Williams, 2013). This study focusses on active uses of Twitter, i.e. why people post on Twitter, which can also indicate which topics Twitter users wish to communicate about during crises.

Whiting and Williams (2013) identified ten different reasons people use social media in general, both active (i.e. why people post) and passive (i.e. why people read). From most to least frequent, they are social interaction, information seeking, passing time, entertainment, relaxation, communicatory utility, convenience utility, expression of opinions, information sharing, and surveillance/knowledge about others. However, it might be that the uses and gratifications of social media differ in times of crises.

Acar and Muraki (2011) used a qualitative analysis in order to identify the most prevalent active uses of Twitter following the 2011 tsunami in Japan. They found that in both the directly and indirectly affected areas, Twitter was mainly used to spread warnings, to request for help, to report about oneself and the environment, and to express concerns and condolences. Even though this studies provides an interesting insight in how social media use is different during crises than normally, the categorization is quite narrow.

Takahashi, Tandoc Jr. and Carmichael (2015) made use of a more extended array of active Twitter uses for analyzing Tweets during a typhoon in the Philippines. They identified nine different content types (i.e. nine different uses of Twitter): personal reporting, secondhand reporting, requesting help, coordinating relief, providing counseling, criticizing government, memorializing, discussing causes, and reconnecting community members. Based on their analysis they stated that, during a crisis, Twitter is mostly used for supplying the most recent news on the subject (secondhand reporting), for expressing concern towards the bereaved (memorializing), and for managing donations and offers for voluntary help (coordinating relief). Together these amounted to 90% of the Tweets that were analyzed.

For their study on the use of Twitter during the 2009 H1N1 (i.e. swine flu) outbreak, Chew and Eysenbach (2010) used the following content categories: resource, personal experience, personal opinion and interest, jokes/parody, marketing, and spam (i.e. tweets unrelated to H1N1). The most dominant category was resource, followed by personal experiences and personal opinion.

The categories from Chew and Eysenbach (2010) largely coincide with the categories from Takahashi et al. (2015), e.g. resource and secondhand reporting, personal experience and personal reporting. One of the main additions to the categorization of Takashi et al. (2015) is the jokes/parody category. However, it could also be interesting to see if jokes or any other type of humor are also present in other content categories, instead of looking at it as a separate category. This study will therefore analyze this relation between humor on the one hand and content type on the other hand.

**Types of users.** Next to the importance of identifying the uses of (social) media, studies have also emphasized the importance of linking these content types to different audience groups (Houston, et al., 2014; Katz, 1995; Whiting & Williams, 2013). Whiting and Williams (2013) state that this is a vital step in understanding the audience, which will help in adjusting content to the target group. According to Houston et al. (2014), one should always aim at understanding who post on social media, before trying to understand what they post.

Takahashi et al. (2015) recognized six different types of users who contribute to the dialogue during crises: individuals, celebrities, journalists, news organizations, governments and NGOs. Combining it with their analysis of content types, they found that journalists, news organizations and governments mostly used their tweets for secondhand reporting, individuals and celebrities mostly for memorializing, and NGOs mostly for coordinating relief.

Based on social media literature, Houston et al. (2014) found the following users: individuals, communities, organizations, governments and news media. The biggest addition to Takahashi et al. (2015) is the category of communities, which Houston et al. (2014) define as groups of citizens who are from the same geographic area or share the same views or thoughts. For the rest, the categorizations are largely the same.

In order to fully understand who posts on Twitter, it is also interesting to find out which types of Twitter users are more likely to use humor. This will also help in further discovering the use of humor during crises. Even though it might be logical to assume that individuals use more humor than journalists, it seems like no studies have confirmed this. Therefore, this study will also analyze the relation between humor on the one hand and user type on the other hand.

**The use of humor over time.** A final step in understanding the use of humorous tweets during crises, is by looking at how this changes over time. Many studies have established a relation between time and humor (Chew & Eysenbach, 2010; McGraw, Williams, & Warren, 2014; Spence, Lachlan, Lin, & Del Greco, 2015). Both Chew and Eysenbach (2010) and Spence et al. (2015) found that the use of humor in tweets decreased as the crisis developed. For the H1N1 outbreak, as studied by Chew and Eysenbach (2010), the use of humor dropped from 22% to 13% in seven months' time, while for hurricane Sandy, as studied by Spence et al. (2015), the use of humor already decreased from 20% to 10% in four days.

McGraw, Williams and Warren (2014) found a slightly different relation for the perception of humor. They analyzed a longer time span of tweets from before, during and after the impact of hurricane Sandy. The research showed that following the impact, there was an increase in perceived humor, leading to a peak, and finally a decrease again. They explained this pattern with the *benign violation theory*, which states that a situation can only be funny when it is both threatening and gentle at the same time. The authors explain this using an example of tickling. Being tickled by a stranger is not funny because it is too threatening, and being tickled by oneself is not funny because it is too gentle. The same can be applied to the relation between humor and time. At the beginning, a natural disaster, virus outbreak or other crisis is too violating to be funny. As the temporal distance starts to increase and takes away some of the threat, the perception of humor increases. The perception keeps on increasing till the situation becomes too benign, i.e. not threatening enough to be funny.

No research seems to have been done to confirm if the benign violation theory can also be applied to the active use of humor. Moreover, it could also be interesting to see if the different types of humor used change during the development of a crisis, or if the content type of tweets changes. Therefore, this research will also look into the relation between time on the one hand and content type and humor type on the other hand.

### Research questions

Previous studies have established clear categorizations for types of humor, and for types of social media content and users during crises. Also, many research has been done on the relation between humor and time. However, there seems to be a lack of research uniting these variables. This study intends to close this gap by examining the question: **To what extent is the type of humor in Tweets related to the development of the Ebola crisis?**

The research question will be answered based on several sub questions. These involve the variables of user type, content type and time.

SQ1. How does user type correlate with type of humor?

SQ2. How does content type correlate with type of humor and the development of the Ebola crisis?

## Method

### Materials

The research question was answered by using a corpus of 282.158 tweets from the Ebola crisis, collected between 22 March 2014 and 1 October 2015 by using the hashtag #ebola. Of this corpus, 10.000 tweets were randomly selected for coding. After removing the doublecoded tweets that were used to calculate the inter-rater reliability, 9033 single tweets remained for the statistical treatment.

## Procedure

The coding was done by a group of 23 final-year Communication and Information Studies students, whose inter-rater reliability was calculated by means of a Cohen's Kappa test.

**Types of humor.** First of all, this research required a clear definition of humor. Humor is not easily definable in terms that are clear, discernible, explanatory and consistent. Mollema et al. (2015) defined humor as "a message that is funny or that expresses sarcasm", which is clear, but not explanatory enough. McGraw, Williams and Warren (2014) explained humor to be "a psychological response characterized by amusement and the tendency to laugh". This definition seemed to be more explanatory, but did not make it easier for the coders to recognize humor in Tweets.

Therefore, it was better to focus on a clear definition and categorization for the nominal variable 'type of humor'. This study used the types of humor from Hay (1995): anecdotes, fantasy, insult, irony, jokes, observational, quote, role play, self-deprecation, vulgarity, wordplay and other (Table 1).

The interrater reliability of the variable 'type of humor' was unsatisfactory: $\kappa = .31$, $p < .001$. This means we have to be cautious with interpreting the results.

Table 1. Types of humor based on the categories from Hay (1995)

| Type of humor | Definition |
|---|---|
| Anecdote | A story that has a funny element or is told in a funny way. |
| Fantasy | An imaginary situation that would be amusing if it were true. |
| Insult | A negative comment about someone else that is either funny because it is not truly genuine or because the audience did not see it coming |
| Irony | A comment with which the speaker actually means the exact opposite. |
| Joke | A funny comment or riddle that has a punchline and often comes in a recognizable format (e.g. question/answer). |
| Observational | A humorous remark about something the speaker sees or hears. |
| Quote | A literal (and funny) recital of someone else's joke or comment. |
| Roleplay | A reenactment of another person in a funny way. |

| | |
|---|---|
| Self-deprecation | An insulting joke of which the speaker himself is the subject. |
| Vulgarity | A dirty joke about sex or body functions. |
| Wordplay | The use of a word in a different context, making it more humorous. |
| Other | Any other type of humor. |

**User type and content type.** For the nominal variables 'user type' and 'content type', the categorizations from Takahashi et al. (2015) were used. The different user types they identified are individuals, celebrities, journalists, news organizations, governments, and NGOs. The current study used a slight adaptation, grouping journalists and news organizations and broadening NGOs to organizations (Table 2). In order to classify the different users, the description from their Twitter profile was used.

The interrater reliability for the variables 'user type' was unsatisfactory: $\kappa = .46$, $p < .001$. This means we have to be cautious with interpreting the results.

Table 2. Categories of user types based on Takahashi et al. (2015)

| **User types** | **Coding criteria** |
|---|---|
| Civilians | Username and tweet show that the user writes from a personal perspective, and is not known as a celebrity or journalist. |
| Celebrities | User is verified and/or known to the coder as a celebrity. |
| Journalists | User is known to the coder as a journalist, tweet contains news or profile description mentions news or journalism. |
| Governments | Profile is verified, profile description states that it is a government, username or profile description mentions the name of a country or a city. |
| Organization | Profile description or username states it is a non-profit organization or a company. |
| Miscellaneous | User cannot be categorized as another user type. |

The content categories from Takahashi et al. (2015) are reporting (secondhand), memorializing, coordinating relief, reporting (personal), discussing causes, reconnecting, criticizing government, requesting help, and providing counselling (Table 3).

The interrater reliability for the variables 'content type' was unsatisfactory: $\kappa = .46$, $p < .001$. This means we have to be cautious with interpreting the results.

Table 3. Types of social media content during a disaster based on Takahashi et al. (2015)

| **Type of content** | **Definition** |
|---|---|
| Reporting on the situation from a personal perspective | Giving firsthand information about disaster and oneself, usually in a personal yet informative tone. |
| Reporting on the situation (secondhand reporting) | Giving secondhand information and news about disaster, usually in an informative tone. |
| Requesting help | Directly demanding help for oneself, usually in a personal and emotional tone. |
| Coordinating relief efforts | Listing ways for volunteering or donating and organizing offers for help, usually in a positive, motivational and slightly informative tone. |
| Providing mental counseling | Giving advice to victims on a psychological level, usually in a positive and conversational tone. |
| Criticizing the government | Expressing opinions about the government's or other organizations' involvement, usually in a negative and critiquing tone. |
| Expressing well wishes and memorializing | Bonding with victims on a personal and emotional level, usually in an empathetic and pitiful, yet positive tone. |
| Discussing causes | Looking for an explanation together, usually in a serious and slightly informational tone. |
| (Re)connect community members | Showing and stimulating recovery of interpersonal relations, usually in a positive, solution-oriented and slightly emotional tone. |
| Miscellaneous | Does not fit in any other category. |

**Time.** For measuring the nominal variable 'time', the tweets were divided in seven time periods, based on quarters of a year. The first time period only covered 22 March till 31 March 2014, followed by 1 April till 30 June 2014, 1 July till 30 September 2014, 1 October till 31 December 2014, 1 January till 31 March 2015, 1 April till 30 June 2015, and the last period – 1 July till 1 October 2015 – also included the single tweet from 1 October.

**Statistical treatment**

In order to answer the research question and the sub questions, several Chi-square tests were done.

## Results

The main purpose of this study was to investigate whether the type of humor in Tweets is related to the development of the Ebola crisis. The sub questions were meant to investigate the relation between user and content types and type of humor, as well as between content types and the development of the Ebola crisis.

The main research question was: ‘To what extent is the type of humor in Tweets related to the development of the Ebola crisis?’ In order to answer this question, a Chi-square test was done, which analyzed the relation between time period and type of humor. Figure 1 displays the different time periods and the percentage of tweets within those periods that contained humor in general. There was a general increase in humorous tweets from March 2014 till November 2014, after which it declined again (Figure 1). The only exception was the July – September 2014 period, in which there was a slight decrease in humorous tweets.

Figure 1. Percentage of humorous tweets per time period

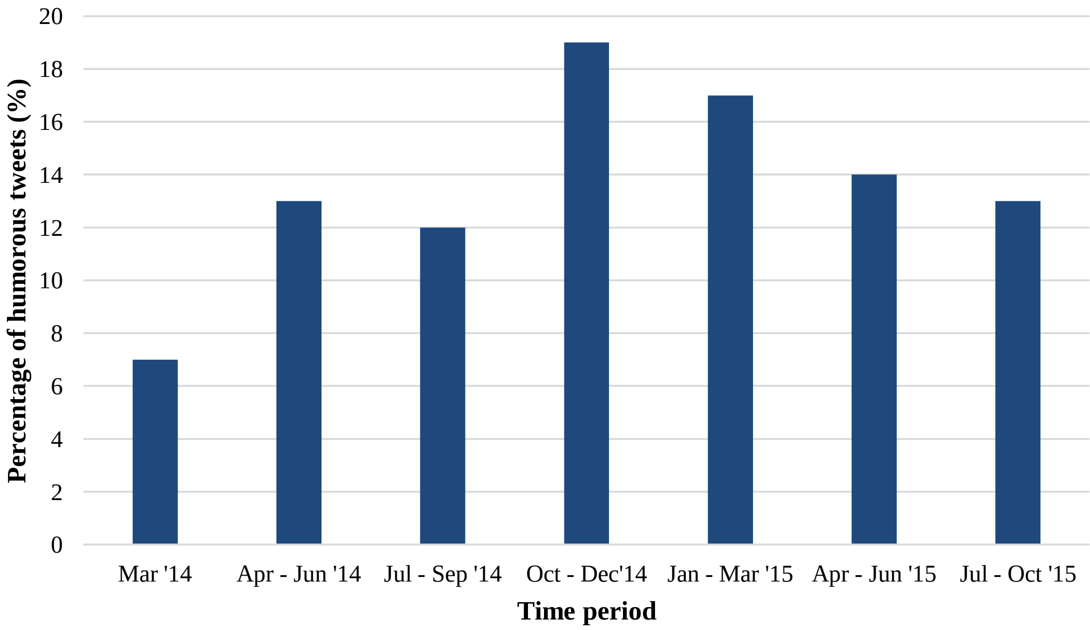


Table 4 shows the crosstabs for time period and humor type, with percentages and standardized residuals. A Chi-square test showed a significant relation between type of humor and user type ($\chi^2$ (72) = 135.97, *p* <.001). Positive standardized residuals (*SR*) larger than 2 and negative SRs smaller than -2 indicated where this significant relation came from. As can be seen in Table 4, in the April – June 2014 period there were more humorous tweets based on quotes than expected (*SR* = 2.1). In the July – September 2014 period there were less tweets with insults (*SR* = -2.9), jokes (*SR* = -2.3), observing humor (*SR* = -2.3), self-depreciation (*SR* = -2.0) and miscellaneous types of humor (*SR* = -3.2) than expected, and more tweets without humor (*SR* = 2.4). In the October – December 2014 period there were more tweets with observing humor (*SR* = 2.5), jokes (*SR* = 2.2), and miscellaneous types of humor (*SR* = 2.3), as well as more tweets categorized as containing no humor (*SR* = -2.0). Finally, in the April – June 2015 period there were more tweets containing self-depreciation (*SR* = 3.1) than expected.

In the March 2014, the January – March 2015 and the July – October 2015 periods there were no categories that contained more or less tweets than expected.

Table 4. Percentages and standardized residuals of types of humor per time period (% within time period)

| Humor type | 22/3/14-31/3/14 | | 1/4/14-30/6/14 | | 1/7/14-30/9/14 | | 1/10/14-31/12/14 | | 1/1/15-31/3/15 | | 1/4/15-30/6/15 | | 1/7/15-1/10/15 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | % | *SR* | % | *SR* | % | SR | % | *SR* | % | *SR* | % | *SR* | % | *SR* |
| Anecdote | 2 | 0.9 | 0 | -1.4 | 1 | -0.7 | 1 | 1.1 | 1 | 0.0 | 0 | -1.1 | 1 | -0.8 |
| Insult | 0 | -1.0 | 2 | -0.4 | 2 | -2.9* | 3 | 1.7 | 3 | 1.3 | 2 | -0.7 | 4 | 1.0 |
| Fantasy | 0 | -0.5 | 0 | -1.1 | 0 | -1.6 | 1 | 1.1 | 1 | 1.0 | 1 | 0.1 | 1 | -0.4 |
| Joke | 0 | -0.7 | 1 | -0.2 | 1 | -2.3* | 2 | 2.2* | 1 | -0.3 | 1 | -0.7 | 1 | -1.0 |
| Irony | 2 | 0.0 | 2 | -0.2 | 2 | -0.4 | 3 | 1.5 | 2 | -1.3 | 1 | -1.8 | 1 | -1.8 |
| Observing | 0 | -0.7 | 1 | -0.8 | 1 | -2.3* | 2 | 2.5* | 1 | -0.2 | 0 | -1.2 | 0 | -1.6 |
| Quote | 0 | -0.3 | 1 | 2.1* | 0 | 0.4 | 0 | -1.0 | 1 | 1.2 | 0 | -0.9 | 1 | 0.6 |
| Role play | 0 | -0.2 | 0 | -0.5 | 0 | -1.8 | 0 | 1.9 | 0 | -0.8 | 0 | -0.6 | 0 | -0.5 |
| Vulgarity | 0 | -0.3 | 0 | -0.7 | 0 | -1.1 | 0 | 0.4 | 0 | 0.4 | 1 | 1.5 | 1 | 0.6 |
| Wordplay | 0 | -0.5 | 0 | -1.0 | 1 | 0.7 | 1 | -0.1 | 1 | 0.0 | 1 | 0.5 | 0 | -1.1 |
| Self-depr. | 0 | -0.3 | 0 | -0.6 | 0 | -2.0* | 0 | 1.1 | 0 | -0.3 | 1 | 3.1* | 0 | -0.7 |
| Misc. | 2 | -1.0 | 6 | -0.1 | 5 | -3.2* | 7 | 2.3* | 6 | 0.2 | 6 | 0.1 | 6 | 0.2 |
| None | 93 | 0.7 | 87 | 0.5 | 88 | 2.4* | 81 | -2.0* | 83 | -0.1 | 86 | 0.5 | 87 | 0.6 |

* Standardized residual is larger than 2.0 or smaller than -2.0

The first sub question was: ‘How does user type correlate with type of humor?’. In order to answer this question, a Chi-square test was done, which analyzed the relation between user type and type of humor. Table 5 displays the different user types and the percentage of their tweets that contained humor in general; Table 6 shows the crosstabs for user type and humor type, with percentages and standardized residuals. A Chi-square test showed a significant relation between type of humor and user type ($\chi^2$ (60) = 2508.19, *p* <.001). Positive standardized residuals larger than 2 and negative SRs smaller than -2 indicated where this significant relation came from.

Table 5. Percentage of humorous tweets per user type

| | Percentage of humorous tweets |
|---|---|
| Government | 40% |
| Civilian | 25% |
| Celebrity | 20% |
| Organization | 3% |
| Journalism | 2% |
| Misc. | 10% |

The user types that used relatively more humor in their tweets were governmental users, civilians and celebrities (Table 5). As can be seen in Table 6, governmental users scored higher than expected on tweets containing anecdotes (*SR* = 41.3), and lower on tweets containing no humor (*SR* = -2.9). Civilians scored higher on insults (*SR* = 7.9), irony (*SR* = 6.7), observations (*SR* = 5.4), jokes (*SR* = 5.1), fantasy (*SR* = 4.3), wordplay (*SR* = 3.0), role play (*SR* = 2.0), and miscellaneous types of humor (*SR* = 8.0), but low on anecdotes (*SR* = -3.0) and on tweets containing no humor (*SR* = -6.5). Celebrities scored higher than expected on irony (*SR* = 3.9).

The user types that used relatively few humor were organizations, journalistic users and miscellaneous users (Table 5). As can be seen in Table 6, all three scored higher than expected on tweets containing no humor (*SR* = 2.8; *SR* = 7.3; *SR* = 2.5). Next to that, organizations scored low on insults (*SR* = -3.1), irony (*SR* = -2.4), jokes (*SR* = -2.1), observing humor (*SR* = -2.1), anecdotes (*SR* = -2.0), and miscellaneous types of humor (*SR* = -3.4), but high on quotes (*SR* = 2.9). Journalistic users scored low on insults (*SR* = -7.0), irony (*SR* = -7.0), jokes (*SR* = -4.7), observing (*SR* = -4.6), fantasy (*SR* = -3.9), anecdotes (*SR* = -3.7), wordplay (*SR* = -2.8), vulgarity (*SR* = -2.4), self-depreciation (*SR* = -2.2), and miscellaneous types of humor (*SR* = -9.0). Miscellaneous users scored low on tweets containing insults (*SR* = -3.8), observing humor (*SR* = -2.9), irony (*SR* = -2.7), fantasy (*SR* = -2.0), and jokes (*SR* = -2.0).

Table 6. Percentages and standardized residuals of types of humor per user type (% within user type)

| Humor type | Celebrity | | Civilian | | Organization | | Journalism | | Government | | Misc. | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | % | *SR* | % | *SR* | % | SR | % | *SR* | % | *SR* | % | *SR* |
| Anecdote | 3 | 1.3 | 1 | -3.0* | 0 | -2.0* | 0 | -3.7* | 37 | 41.3* | 1 | -1.5 |
| Insult | 0 | -0.9 | 4 | 7.9* | 0 | -3.1* | 0 | -7.0* | 0 | -1.8 | 1 | -3.8* |
| Fantasy | 0 | -0.5 | 1 | -1.6 | 0 | -1.6 | 0 | -3.9* | 0 | -0.9 | 0 | -2.0* |
| Joke | 0 | -0.6 | 2 | 5.1* | 0 | -2.1* | 0 | -4.7* | 0 | -1.2 | 1 | -2.0* |
| Irony | 13 | 3.9* | 4 | 6.7* | 1 | -2.4* | 0 | -7.0* | 0 | -1.8 | 1 | -2.7* |
| Observing | 0 | -0.6 | 2 | 5.4* | 0 | -2.1* | 0 | -4.6* | 0 | -1.2 | 0 | -2.9* |
| Quote | 0 | -0.3 | 0 | 0.8 | 1 | 2.9* | 0 | -0.8 | 0 | -0.6 | 0 | -1.9 |
| Role play | 0 | -0.2 | 0 | 2.0* | 0 | -0.7 | 0 | -1.6 | 0 | -0.4 | 0 | -1.3 |
| Vulgarity | 0 | -0.3 | 0 | 1.9 | 0 | -1.0 | 0 | -2.4* | 0 | -0.6 | 0 | 0.2 |
| Wordplay | 0 | -0.4 | 1 | 3.0* | 0 | -1.4 | 0 | -2.8* | 0 | -0.8 | 0 | -1.1 |
| Self-depr. | 0 | -0.3 | 0 | 0.9 | 0 | -0.9 | 0 | -2.2* | 0 | -0.5 | 0 | 1.8 |
| Misc. | 3 | -0.6 | 9 | 8.0* | 2 | -3.4* | 1 | -9.0* | 2 | -1.7 | 5 | -1.2 |
| None | 80 | -0.2 | 75 | -6.5* | 97 | 2.8* | 98 | 7.3* | 60 | -2.9* | 90 | 2.5* |

* Standardized residual is larger than 2.0 or smaller than -2.0

The second sub question was: ‘How does content type correlate with type of humor and the development of the Ebola crisis?’. In order to answer this question, two Chi-square tests were done, which analyzed the relation between content type on the one hand and type of humor and time period on the other hand. First the relation between content type and type of humor will be discussed, followed by the relation between content type and time period.

Table 7 displays the different content types and the percentage of their tweets that contained humor in general; Table 8 shows the crosstabs for user type and humor type, with percentages and standardized residuals. A Chi-square test also showed a significant relation between type of humor and content type ($\chi^2$ (108) = 2941.54, *p* <.001). Positive standardized residuals (*SR*) larger than 2 and negative SRs smaller than -2 indicated where this significant relation came from.

Table 7. Percentage of humorous tweets per content type

| Content type | Percentage of humorous tweets |
|---|---|
| First hand | 40% |
| Criticize government | 24% |
| Reconnecting members | 22% |
| Discuss causes | 20% |
| Requesting help for self | 14% |
| Memorializing | 10% |
| Providing counseling | 9% |
| Coordinating relief for others | 5% |
| Second hand | 4% |
| Misc. | 44% |

The content types that contained relatively more humorous tweets were ‘first hand reporting,’ ‘criticize government,’ ‘reconnecting members,’ ‘discuss causes,’ ‘requesting help for self,’ ‘memorializing’ and ‘miscellaneous’ (Table 7). As can be seen in Table 8, tweets containing first hand reporting scored higher than expected on humorous tweets containing anecdotes (*SR* = 26.2), irony (*SR* = 7.6), quotes (*SR* = 4.1), fantasy (*SR* = 2.3), jokes (*SR* = 2.3), and vulgarity (*SR* = 2.1), and lower than expected on tweets containing no humor (*SR* = -5.0). Tweets criticizing the government scored high on irony (*SR* = 10.0) and insults (*SR* = 4.6), and low on tweets containing no humor (*SR* = -2.0). Tweets reconnecting members only scored high on vulgarity (*SR* = 2.7), tweets discussing causes only on jokes (*SR* = 4.5), tweets requesting help for oneself only on self-depreciation (*SR* = 2.1), and tweets memorializing victims only on jokes (*SR* = 2.4). The latter had a lower score than expected for tweets containing insults (*SR* = -3.0). Finally, tweets from the miscellaneous content category scored high on insults (*SR* = 17.0), observing (*SR* = 9.6), fantasy (*SR* = 8.7), wordplay (*SR* = 6.3), jokes (*SR* = 5.6), vulgarity (*SR* = 5.6), irony (*SR* = 4.6), role play (*SR* = 4.0), self-deprecation (*SR* = 3.4), and miscellaneous types of humor (*SR* = 22.1), while scoring lower than expected on tweets containing no humor (*SR* = -13.2).

The content types that contained relatively few humor were ‘coordinating relief for others’ and ‘second hand reporting’ (Table 7). As can be seen in Table 8, both scored higher than expected on tweets containing no humor (*SR* = 2.5; *SR* = 9.6). Next to that, tweets that coordinated relief for others scored lower than expected on tweets containing insults

Table 8. Percentages and standardized residuals of types of humor per content type (% within content type)

| Humor type | Coordinating relief | | Criticize government | | Discuss causes | | First hand | | Memorializing | | Providing counseling | | Reconn. members | | Requesting help | | Second hand | | Misc. | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | % | *SR* | % | *SR* | % | *SR* | % | *SR* | % | *SR* | % | *SR* | % | *SR* | % | *SR* | % | *SR* | % | *SR* |
| Anecdote | 0 | -1.4 | 0 | -1.5 | 1 | 0.1 | 15 | 26.2* | 0 | -1.9 | 1 | -0.7 | 0 | -0.6 | 0 | -0.9 | 0 | -4.7* | 1 | -1.2 |
| Insult | 0 | -3.1* | 6 | 4.6* | 3 | 0.1 | 2 | -0.4 | 0 | -3.0* | 1 | -1.3 | 5 | 0.9 | 0 | -1.3 | 0 | -10.7* | 9 | 17.0* |
| Fantasy | 0 | -1.6 | 0 | -0.9 | 1 | 0.6 | 2 | 2.3* | 0 | -0.9 | 1 | -0.3 | 0 | -0.5 | 1 | 0.8 | 0 | -5.5* | 2 | 8.7* |
| Joke | 1 | -0.7 | 1 | -0.6 | 5 | 4.5* | 3 | 2.3* | 3 | 2.4* | 1 | -0.2 | 2 | 0.7 | 3 | 1.3 | 0 | -5.7* | 3 | 5.6* |
| Irony | 1 | -1.3 | 9 | 10.0* | 3 | 0.7 | 9 | 7.6* | 1 | -1.1 | 2 | -0.8 | 2 | 0.0 | 4 | 1.0 | 1 | -8.0* | 4 | 4.6* |
| Observing | 0 | -1.6 | 2 | 1.6 | 0 | -1.5 | 1 | -0.5 | 1 | 0.5 | 0 | -1.5 | 2 | 0.8 | 0 | -0.9 | 0 | -5.9* | 3 | 9.6* |
| Quote | 0 | 0.0 | 0 | -1.2 | 0 | -0.7 | 1 | 4.1* | 0 | 0.1 | 0 | -0.7 | 0 | -0.3 | 0 | -0.4 | 0 | 0.4 | 0 | -1.1 |
| Role play | 0 | -0.7 | 0 | 1.6 | 0 | -0.5 | 0 | -0.7 | 0 | -0.7 | 0 | -0.5 | 0 | -0.2 | 0 | -0.3 | 0 | -2.4* | 0 | 4.0* |
| Vulgarity | 0 | -1.0 | 0 | -0.4 | 0 | -0.7 | 1 | 2.1* | 0 | -1.0 | 0 | -0.7 | 2 | 2.7* | 0 | -0.4 | 0 | -3.6* | 1 | 5.6* |
| Wordplay | 0 | -0.7 | 0 | -1.1 | 1 | 1.0 | 1 | 0.1 | 0 | -1.3 | 1 | 1.0 | 0 | -0.5 | 0 | -0.6 | 0 | -3.6* | 2 | 6.3* |
| Self-depr. | 0 | -0.9 | 0 | -0.2 | 0 | -0.6 | 1 | 1.3 | 0 | 0.3 | 0 | -0.7 | 0 | -0.3 | 1 | 2.1* | 0 | -3.0* | 1 | 3.4* |
| Misc. | 1 | -3.7* | 5 | -1.0 | 6 | -0.1 | 6 | 0.3 | 4 | -1.7 | 3 | -1.7 | 7 | 0.3 | 4 | -0.6 | 2 | -12.5* | 18 | 22.1* |
| None | 96 | 2.5* | 76 | -2.0* | 80 | -0.5 | 60 | -5.0* | 90 | 1.3 | 91 | 1.2 | 78 | -0.4 | 86 | 0.2 | 96 | 9.6* | 56 | -13.2* |

* Standardized residual is larger than 2.0 or smaller than -2.0

(*SR* = -3.1) and miscellaneous types of humor (*SR* = -3.7). Tweets containing second hand reporting scored low on insults (*SR* = -10.7), irony (*SR* = -8.0), observing humor (*SR* = -5.9), jokes (*SR* = -5.7), fantasy (*SR* = -5.5), anecdotes (*SR* = -4.7), vulgarity (*SR* = -3.6), wordplay (*SR* = -3.6), self-depreciation (*SR* = -3.0), role play (*SR* = -2.4), and miscellaneous types of humor (*SR* = -12.5).

Only tweets providing counseling had an average score for all the humor types.

Table 9 shows the crosstabs for time period and content type, with percentages and standardized residuals. A Chi-square test showed a significant relation between time period and content type ($\chi^2$ (54) = 285.08, $p$ <.001). Positive standardized residuals (*SR*) larger than 2 and negative SRs smaller than -2 indicated where this significant relation came from.

As can be seen in Table 9, in the March 2014 period there were more tweets containing second hand reporting than expected (*SR* = 2.3), while there were fewer tweets from the miscellaneous category (*SR* = -2.5). In July – September 2014 there were more second hand reporting tweets (*SR* = 5.3), but less tweets from the miscellaneous category (*SR* = -7.2). In the October – December 2014 period, there were more tweets than expected that coordinated relief (*SR* = 2.3), criticized the government (*SR* = 2.3), and more miscellaneous tweets (*SR* = 5.8), but fewer second hand reporting tweets (*SR* = -6.3). In January – March 2015 there were more second hand reporting tweets (*SR* = 2.0), but less tweets criticizing the government (*SR* = -2.7). In April – June 2015 there were more second hand reporting tweets (*SR* = 3.1), but less tweets criticizing the government (*SR* = -2.6), coordinating relief (*SR* = -2.5), and providing counseling (*SR* = -2.0). Finally, in the July – October 2015 period there were more tweets containing second hand reporting (*SR* = 3.5), but less tweets coordinating relief (*SR* = -2.7), criticizing the government (*SR* = -2.2), and discussing causes (*SR* = -2.1).

Only in the April – June 2014 period there were no categories that contained more or less tweets than expected.

Table 9. Percentages and standardized residuals of content types per time period (% within time period)

| Content type | 22/3/14-31/3/14 % | *SR* | 1/4/14-30/6/14 % | *SR* | 1/7/14-30/9/14 % | SR | 1/10/14-31/12/14 % | *SR* | 1/1/15-31/3/15 % | *SR* | 1/4/15-30/6/15 % | *SR* | 1/7/15-1/10/15 % | *SR* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Coordinating relief | 5 | 0.2 | 3 | -1.0 | 4 | -0.8 | 5 | 2.3* | 3 | -1.3 | 1 | -2.5* | 1 | -2.7* |
| Criticize government | 0 | -1.6 | 8 | 1.1 | 6 | -0.6 | 7 | 2.3* | 3 | -2.7* | 2 | -2.6* | 2 | -2.2* |
| Discuss causes | 0 | -0.9 | 2 | -0.5 | 2 | -0.3 | 2 | 1.0 | 2 | -0.3 | 2 | -0.3 | 0 | -2.1* |
| First hand | 2 | -0.5 | 3 | -0.9 | 4 | -0.3 | 4 | 0.7 | 4 | 0.0 | 4 | 0.0 | 2 | -1.3 |
| Memorializing | 7 | 1.1 | 1 | -1.9 | 4 | 0.8 | 4 | 0.6 | 3 | -0.5 | 2 | -1.4 | 1 | -1.9 |
| Providing counseling | 2 | 0.1 | 2 | 0.0 | 2 | 0.1 | 2 | 1.0 | 1 | -1.3 | 0 | -2.0* | 1 | -0.8 |
| Reconn. members | 0 | -0.4 | 1 | 0.2 | 0 | -1.1 | 1 | 1.6 | 0 | -1.6 | 0 | -0.2 | 0 | -1.0 |
| Requesting help | 0 | -0.6 | 1 | 0.4 | 1 | -0.3 | 1 | 0.9 | 0 | -1.7 | 1 | -0.1 | 1 | -0.5 |
| Second hand | 79 | 2.3* | 60 | 1.3 | 61 | 5.3* | 47 | -6.3* | 59 | 2.0* | 67 | 3.1* | 70 | 3.5* |
| Misc. | 5 | -2.5* | 20 | -0.9 | 17 | -7.2* | 27 | 5.8* | 24 | 0.2 | 21 | -1.0 | 22 | -0.6 |

* Standardized residual is larger than 2.0 or smaller than -2.0

## Conclusion/discussion

The main research question looked at the relation between type of humor and the development of the Ebola crisis. Plotting humor over time displayed a general increase and decrease in the use of humor. It appeared that there was an increase in tweets containing humor from March 2014 till November 2014, leading to a peak about half a year after the start of the crisis, followed by a steady decrease until October 2015. This is in line with the benign violation theory from McGraw, Williams and Warren (2014), which states that the development of humor after the crisis's impact always follows a similar pattern of an initial increase followed by a decrease.

The benign violation theory also offers an explanation for the pattern discovered in this research. It is likely that the Ebola crisis became less violating as time passed, which made it more acceptable to make jokes about the virus. This lead to an increase in humorous tweets, up until the peak in the October – December 2014 period. However, after a certain point it became too benign, which also made it less funny. This lead to a decrease in humorous tweets.

Interestingly, the July – September 2014 period was the only exception to this pattern. Following the benign violation theory, one would expect an increase in humorous tweets in this period, but instead there was a slight decrease of 1 percentage point. Even though this difference might seem small, the significant negative standardized residuals for insults, jokes, observing humor, self-depreciation and miscellaneous types of humor in that period confirm that there is indeed a remarkable exception from the pattern.

A possible explanation to this odd finding can be found in the traditional media. In a timeline from The Guardian depicting the biggest news events about Ebola it can be seen that the World Health Organization (WHO) declared Ebola as an “international health emergency” on 8 August 2014 (Davis, 2014). The statement could have given the violation of the crisis a new boost, which caused the subject to be temporarily less funny. This is especially relevant because the corpus was mostly made up of tweets by Dutch users, for whom the crisis only came close when it was announced as international.

Looking at the specific types of humor, a Chi-square test found a significant relation for the distribution of types of humor over time. Quotes were the humor type that peaked the first (April – June 2014). Around this time, many users might not have been sure whether it was already acceptable to make jokes or not. Therefore, it could have been less intimidating to cite someone else’s joke instead of one’s own. Moreover, it could have also originated from a lack of creativity in the beginning, meaning users cited other’s jokes because they could not come up with one themselves.

Tweets containing self-depreciation peaked last, in the April – June 2015 period, while the rest of the humorous tweets was already decreasing. Further research is needed to come up with logical explanations for this finding.

The first sub question focused on the relation between user types and types of humor. The Chi-square test found a significant relation, meaning that there is indeed a relation between the two variables. As presented earlier, governmental users, civilians and celebrities make the most use of humor in their tweets. For civilians this is not completely unexpected, as they do not face any restrictions from social media policies that the other user types often do have.

For the same reason of having restrictions from social media policies, it is quite remarkable to see that celebrities score higher than expected on irony and governmental users higher on anecdotes. Both findings do not seem very likeable, and could therefore originate from a mistake during the coding process. Irony is generally hard to detect, and especially in social media (Reyes, Rosso, & Buscaldi, 2012). Possibly, the coders have also incorrectly detected irony in several cases. It should also be noted that the amount of tweets posted by celebrities was extremely small (30 tweets), so any mistake made in the coding could strongly effect the results.

For anecdotes it should be noted that the coders used a special software program designed for the coding process, in which drop down menus were used to select the corresponding category per variable for every tweet. ‘Anecdote’ was the first category on the list, and therefore selected by default. Some of the coders might have forgotten to change the category into the correct one, leading to a high number of tweets categorized as containing anecdotes.

Moreover, as apparent from the results, organizations and journalistic users used humorous tweets the least. These results were as expected, as both users are expected to be more serious in the tweets they post. The only interesting finding was that of organizations posting more humorous tweets based on quotes as expected. However, this was only a very small percentage (1%) of the total tweets posted by organizations. Nonetheless, it could be because of an interpretation mistake made by the coders. Possibly, some students coded it as ‘quote’ when there was a quote in the tweet, instead of when there was a *humorous* quote in the tweet.

When looking at the specific types of humor, it can be seen that almost all categories are mostly used by civilians (insults, irony, observing, jokes, role play, and wordplay). They appear to use insults and irony the most. In insulting tweets, they often used Ebola as a swearword (e.g. “Get Ebola”), whereas in ironic tweets they mostly made fun of news about Ebola (e.g. “So happy that a white guy does not have Ebola anymore”).

The second sub question looked into the relation between content type on the one hand and type of humor and the development of the Ebola crisis on the other hand. The first Chi-square test found a significant relation, meaning that there is indeed a relation between content type and type of humor. To start with, tweets containing first hand reporting, criticizing government, reconnecting members, discussing causes, requesting help for self, and memorializing displayed the highest presence of humor. This is an interesting finding, as most categories are not expected to contain humor, because the category description suggests a more serious tone. The only category where humor could have been expected was that of criticizing the government.

Tweets in the category of first hand reporting contained the most types of humor (anecdotes, fantasy, jokes, irony, quotes, and vulgarity). This could be explained by a possible misunderstanding among the coders. Many interpreted first hand reporting as any tweet about oneself, while it was meant to be only about one's own situation concerning Ebola. Therefore, many (humorous) tweets that probably should have been categorized as miscellaneous, were categorized in first hand reporting.

For the categories of discussing causes and memorializing, it seems like most of the humorous tweets can be assigned to these content categories only when taken literally and by not looking at the meaning of the joke. Discussing causes scored highest on jokes because of tweets such as "Has ISIS already claimed the Ebola epidemic?". Memorializing scored highest on jokes because of tweets such as "Special Ebola representative is called Doctor. Then it will be fine." In both cases, the meaning of the joke would indicate a completely different content category.

Finally, it is highly likely that for categories of reconnecting members and requesting help for self, there have been mistakes made in the coding process. It is impossible to explain where these findings originate from.

The second Chi-square test also found a significant relation for the distribution of content types over time. The category that peaked the first was that of second hand reporting (March 2014). Around this time, there was probably a lot of news about Ebola in traditional media, which could have caused the conversation on Twitter to shift to news, too. What is interesting, however, is that following the peak in March 2014, there were also peaks in July – September 2014, January – March 2015, April – June 2015 and July – October 2015. This is not in accordance with findings from Takahashi et al. (2015), who only found a decrease in second hand reporting. Possibly these multiple peaks coincide with major news in the traditional media, but further research is needed to prove this.

Coordinating relief saw a clear peak in October – December 2014, which is the same time period in which the amount of humorous tweets peaked. This seems contradictory: according to the benign violation theory, humor peaks when the situation has a good balance between being highly threatening and being non-threatening, but one could expect that coordinating relief is at its highest when the situation is highly threatening. One explanation could be that it took some time for the issue to gain social awareness, which then caused a delay in the relief-coordinating actions.

Criticizing the government also saw a clear peak in the October – December 2014 period. This could be explained with the same argument: possibly it took several months for people to form an opinion about the issue and actively participate in the debate. Interestingly, the amount of criticizing comments fell below the average level in all the consecutive time periods. This seems to indicate that the need to criticize the government is easily satisfied.

The biggest flaw in this research is the low interrater reliability for all three the variables. Even though the coders made use of extensive definitions for all the categories, they did not help create a more unanimous coding. It is also highly likely that this low interrater reliability has played a role in some of the odd results as mentioned before.

Another fault in the study's method is that the retweets and duplicates were not removed from the database before coding. Therefore, many tweets now occur more than once in the database, which is likely to have affected the results. If, for example, news tweets generally get more retweets, it will increase the amount of second hand reporting tweets from journalistic users containing no humor.

This research has provided some interesting insights that are useful for further research and for the field of crisis communications. First of all, this study confirms the benign violation theory from McGraw, Williams and Warren (2014), and proves that it can also be applied to health crises such as Ebola. However, it also appeared that certain important news events can give the perceived violation of a crisis a new boost, leading to a temporary drop in the amount of humor used.

Moreover, this study has shown that not every type of humor peaks at the same time. Quotes, for example, are used before other types of humor, feasibly because they are safer and require less creativity. Self-depreciation peaked as the last type of humor. Further research could take a further look into the reasons for these different peak moments.

Furthermore, this study confirmed the expectations that civilians use the most humor, and organizations and journalistic users the least. However, the amount of humor used by celebrities and governments needs some more attention in further research. Also, it might be interesting to split the group of civilians up further, to see if that can give bigger differences in which group uses which type of humor.

Most of the findings concerning content type were highly unexpected and do not seem likely. The only category in which humor occurred and could have also been expected was that of criticizing the government. Further research could try to reproduce this study in such a way that it does give more likely results. Additionally, it could be interesting for further research to find out why the content categories of criticizing the government and coordinating relief peaked in the same period as the amount of humorous tweets.

Overall, the findings of this study offer useful guidelines for deciding how an organization, such as the WHO, a news outlet or a governmental body should participate in the discussion about health crises on Twitter, especially with regard to humor. The outcomes show which users are more likely to use which type of humor, in which discussion topics which type of humor is more prevalent, and when certain discussion topics and humor types are more dominant. This will help those organizations and institutions want to participate in the online discussion in deciding when to use which type of humor and when it is better to be serious.

It is important, however, to realize that the outcomes might not be reliable enough to be taken into practice, based on the fact that the inter-rater reliabilities were so low. Many findings, such as that of governments using a high amount of humor based on anecdotes, seem to be highly unlikely. Future research could try to improve on this by using different humor types, giving the coders a better training and letting more tweets be coded and discussed by multiple coders.

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