Creating interaction in the online political sphere: Which Twitter content triggers response?

Master thesis by
BSc S. van 't Slot

Communication Science
Corporate Communication
University of Twente

Supervisors: First: Dr J. J. van Hoof
Second: Dr J. F. Gosselt

September 18th, 2017

Abstract

Introduction The popularity of social media platforms amongst citizens has led to the presence of politicians who use these platforms to generate their own content, and interact with their voters. Especially interaction on social media is beneficial for politicians as it can be used to keep citizens up to date, to give citizens attention, to entice new people in politics, and to help increase youngsters' political efficacy. However, despite the benefits, interaction remains unexplored in research and it remains unknown what kind of messages and message characteristics can trigger interaction. **Objective** This study aimed at finding out which content from list pullers triggers interaction on Twitter. **Method** A content analysis of all tweets started by thirteen list pullers during the election period of the 2017 Dutch elections (N = 2158) was executed. The analysis consisted of three content categories: topic and issue (topics, visual content, and tweet characteristics), opinion and sentiment (tone, and humour), and structural category (actors). **Results** Results from the topic and issue category showed that more interaction is found in tweets with an international topic (e.g. war/terrorism, or Europe) or a comment on the government and other politicians, whereas tweets with a national topic (e.g. education, or health) triggered less interaction. Tweets with visual content (carrying the corporate social identity of the politician's party) triggered more interaction. The tweet characteristics hashtags and emoticons triggered more interaction, whereas @-mentions and URL's led to less interaction. The opinion and sentiment category showed that a slightly negative tone triggers more interaction, and that humour appeals to Twitter users in the form of likes. The results found for the structural category only show that mentioning international politicians leads to more interaction. **Conclusion** If list pullers aim at triggering interaction with their tweets, they can gain most benefit from focusing on the topic and issue category. Implications for political communication will especially show in the social media strategies of politicians and the involvement of citizens in political communication. Political communication with a focus on interaction will change one-way broadcasting to a dynamic and complex conversation in which more people will be actively involved than ever before.

Keywords Political communication, social media, Twitter, interaction, content analysis

Table of Content

1. Introduction 7
2. Theoretical framework 8
   2.1 Political communication 8
   2.2 Political communication and social media 9
   2.3 Interactivity 11
   2.4 Aspects of interaction on Twitter 12
   2.5 Research goal 17
3. Method 18
   3.1 Context 18
   3.2 Corpus 18
   3.3 Codebook 19
   3.4 Validity and reliability 21
   3.5 Data analysis 22
4. Results 24
   4.1 Topic and issue category 24
   28
   4.2 Opinion and sentiment category 29
   4.3 Structural category 30
   4.4 Additional content 32
5. Discussion 37
   5.1 Interpretation of findings 37
   5.2 Implications for political communication 38
   5.3 Limitations 39
   5.4 Conclusion 39
Literature 40
Appendices 45

1. Introduction

Social media platforms, such as Twitter, provide politicians with the possibility to reach their potential voters independently and personally in a direct manner, and on a regular basis (Vergeer & Hermans, 2013). As a consequence, many politicians are present on social media platforms (Stieglitz & Dang-Xuan, 2013). In practice, politicians mostly use these platforms for one-way communication (Vergeer & Hermans, 2013).

However, using social media platforms as a tool to create interaction with or between citizens could make a substantial difference in elections. After all, Spierings and Jacobs (2014) suggest that interactivity might be the key to the hearts of voters. This is not only because interaction with politicians and other citizens fulfils citizens' desire to be kept up to date and to receive attention (Spierings & Jacobs, 2014). Namely, interaction increases transparency in political affairs and the involvement of citizens in political decision-making processes (Stieglitz & Dang-Xuan, 2013). Moreover, interaction can entice new people in politics (Vergeer, Hermans & Sams, 2011). For example, through interaction on social media politicians are able to reach especially youngsters, and make them enthusiastic about politics and encourage them to vote (Moeller, De Vreese, Esser & Kunz, 2014). Finally, discussing politics with others online is a way for youngsters in particular to increase political efficacy (Moeller et al., 2014).

Graham, Jackson and Broersma's (2014) study on candidate's use of Twitter during election campaigns showed that Twitter is becoming a place where interaction between politicians and citizens can evolve. They suggest that future research should delve into the use of Twitter by citizens with regard to their interaction with politicians. Graham, Broersma, Hazelhoff and Van 't Haar (2013) investigated with whom candidates interact on Twitter, but not which content actually encourages interaction. In addition, Druckman (2004, p. 15) suggested that interpersonal discussions are capable of shaping citizens' voting decisions and that future research would benefit from exploring this subject. Adding to this existing knowledge of politicians' use of Twitter and the discussion on the use of interactivity in political campaigning, this research focuses on what content in messages on Twitter sent by list pullers can trigger interaction from other Twitter users. Therefore, the research question that will be answered is the following:

Which content from list pullers' tweets creates interaction on Twitter?

2. Theoretical framework

The following chapter gives an overview of the existing relevant literature on political communication and interaction on social media. At first, an overview of the history of political communication will be given, followed by a second section on the use of social media in a political context. The third section discusses what is already known about interaction on social media, the advantages and disadvantages of political communication on social media, and the aspects of interaction with regard to Twitter.

2.1 Political communication

In many democracies, political communication has gone through three phases during the post-war period. The first period was during the first two decades after World War II, and is called "the 'golden age' of parties" (Blumler & Kavanagh, 1999, p. 211). During that period, the political arena was dominated by strong parties that were able to get their messages to the media without much difficulty, and they were supported by loyal voters (Blumler & Kavanagh, 1999). It was with difficulty that citizens were able to select the sources that reflected their own political preferences, as the range of sources was very limited (Bennett & Iyengar, 2008). Citizens were only able to expose themselves to content considering preferred parties and candidates during campaigns (Bennett & Iyengar, 2008). This type of campaigning was characterized by the use of newspapers and direct face-to-face communication during rallies and meetings (Vergeer, Hermans & Sams, 2011).

During the 60's, the second period began with the arrival of the limited-channel nationwide television (Vergeer, Hermans & Sams, 2011). Politics were brought into the living rooms of citizens who thereby became more involved in politics (Gurevitch, Coleman & Blumler, 2009). Through television more people were reached than before, enticing new people in politics. Television became a dominant medium for political parties to broadcast their messages. Gurevitch, Coleman, and Blumler (2009) call this the television-politics relationship in which television journalists depend on the content provided by politicians, and politicians depend on being broadcasted. The voters' loyalty to one party was loosening in this period, which was, among other things, due to the less selective news channels that provided voters with a broader scope on politics (Blumler & Kavanagh, 1999). This broader scope included, among other things, recent events and governments' successes and failures.

The third phase is characterized by the broad availability of television and radio channels for political communication (Blumler & Kavanagh, 1999). The computer and the Internet were also introduced in the third phase, both allowing people to search for information and engage in discussions beyond the mass media twenty-four-seven (Blumler & Kavanagh, 1999). The broad availability of media channels led to a more competitive environment in which politicians have to compete for attention from journalists as well as audiences (Blumler & Kavanagh, 1999).

2.2 Political communication and social media

This broad online media environment has many users. For example, in 2011, the platform Facebook had over 800 million users worldwide, and Twitter had 200 million users (Stieglitz & Dang-Xuan, 2013). In January 2017, there were over 1,870 million active Facebook users and over 317 million active Twitter users (Allen, 2017), which shows immense growth of both platforms. On these social media platforms all users are capable of publishing their own content, micro-blogs and weblogs (Stieglitz & Dang-Xuan, 2013). In addition to the possibility to generate one's own content online, the Internet allows users to cooperate, share content, socialize, and network with other users (Stieglitz & Dang-Xuan, 2013; Vergeer & Hermans, 2013). This results in an ever increasing variety and amount of content regarding political affairs on social networking sites (SNSs).

The academic discipline of political communication had already thoroughly researched the traditional mass media, before the rise of the Internet. These days, the Internet has established itself next to the mass media (Dahlgren, 2005). Compared to traditional mass media, the study of online political communication is interesting in that the Internet allows the presence of many more political voices, more ways for political engagement, and an increase in definitions of what constitutes politics (Dahlgren, 2005). However, research also has to take into account the information overload that results from the access of a seemingly limitless amount of sources provided by, among others, politicians, political parties, and individual bloggers (Bennett & Iyengar, 2008).

2.2.1 Use of social media by politicians

With that many spaces of mediation and the growth of social media platforms, there are consequences for politicians. Namely, these days, politicians are forced to engage in "multidimensional impression management" in the broad media environment (Gurevitch, Coleman & Blumler, 2009, p. 173). Thus, politicians started participating on these platforms as well, which led to the presence of many politicians and citizens on SNSs (Stieglitz & Dang-Xuan, 2013).

When politicians use social media, they do that independently. Because the politician is the sender, a politician no longer necessarily depends on assistance by, among others, party officials or journalists determining which events are deemed newsworthy (Klinger & Svensson, 2014; Vergeer, Hermans & Sams, 2011; Vergeer & Hermans, 2013). Furthermore, politicians are able to send as many messages as they would like at any given moment, as SNSs offer fast communication channels at very low costs that are unhindered by national or geographical boundaries (Stieglitz & Dang-Xuan, 2013; Vergeer & Hermans, 2013).

Politicians also use social media because SNSs are networked (Vergeer, Hermans & Sams, 2011). News travels fast within well-connected networks, which is important when a politician wishes to spread a message. The network of a politician serves as a community from which a politician can gain support (Stieglitz & Dang-Xuan, 2013). Within this community, politicians are able to deploy an individualized and personal campaign strategy (Vergeer & Hermans, 2013). Such a strategy could lead to decreasing the psychological distance between politicians and citizens, which again increases the sense of community within the network. Some popular SNSs for individualized campaigning among politicians are Facebook, YouTube, and Twitter (Vergeer, Hermans & Sams, 2011).

2.2.2 Use of social media by citizens in a political context

Social media are part of what Downey and Fenton (2003) call non-mass media or community media. A relevant characteristic of these media is that the production of content is often based on participation by citizens (Downey & Fenton, 2003). In a political context, this results in users of blogs discussing political affairs with other individuals, spreading their political opinion to a wider audience (Baum & Groeling, 2008). With regard to this, it is important to note that users are more likely to share content from sources with a similar ideology instead of content from dissimilar sources (Barberá, Jost, Nagler, Tucker & Bonneau, 2015). Besides discussing and sharing political views, being pro-active online in finding political information, and engaging in campaigns leads to citizens feeling better informed, experiencing political efficacy, and being willing to participate in democratic processes (Gurevitch, Coleman & Blumler, 2009).

2.2.3 Disadvantages of social media in a political context

It is important to acknowledge that the immense growth of social media use and the platforms themselves have some important drawbacks with regard to political communication and political information gathering. The first drawback is that using the Internet for political information gathering generally leads to users avoiding opinion-challenging content and only selecting the information that confirms users' existing points of view (Halberstam & Knight, 2016; Knobloch-Westerwick & Meng, 2009). Consequently, users are unable to form an informed opinion based on a variety of viewpoints, which in turn leads to a more polarized and divided electorate, and to a reduction of political tolerance (Knobloch-Westerwick & Meng, 2009). Klinger and Svensson (2014) refer to the avoidance of opinion-challenging content as selective exposure. Because of this, politicians tend to reach a self-selected audience instead of a general public, and are therefore not addressing new potential voters (Klinger & Svensson, 2014). The second drawback refers to information overload, as the Internet offers an unparalleled amount of easily accessible information to process (Gurevitch, Coleman & Blumler, 2009). In continuation of this, users of the Internet are uncertain of which information they can trust (Gurevitch, Coleman & Blumler, 2009).

2.2.4 Advantages of social media in a political context

Besides drawbacks, using the Internet and social media for political information sharing and gathering comes with many advantages. First, the Internet is beneficial as a source of political information in that it operates twenty-four-seven (Johnson & Kaye, 2000). Second, social media offer users efficient communication at low costs (Kaplan & Haenlein, 2010). Third, sharing information on the Internet is free of the professional and social constraints to provide readers with an accurate and unbiased overview of events, as opposed to television and newspapers, allowing users to share their own opinions without difficulty (Johnson & Kaye, 2000). Fourth, SNSs provide (young) voters with platforms to discuss politics, share information and form an opinion, which increases their internal efficacy with regard to politics (Moeller et al., 2014). Fifth, social media platforms can be used to organize groups (Laroche, Habibi, Richard & Sankaranarayanan, 2012); creating tight communities of followers of a politician. Although the opportunities are not yet being exploited to the full extent, social media platforms offer a relevant sixth benefit. This opportunity regards a feature of SNSs that in the political context can provide more participation and democracy (Stieglitz & Dang-Xuan, 2013), and political engagement (Vergeer, Hermans & Sams, 2011). These are the interactive features of SNSs which allow politicians to directly interact with citizens on social media platforms (Stieglitz & Dang-Xuan, 2013; Vergeer, Hermans & Sams, 2011).

2.3 Interactivity

Social media platforms offer a wide range of possibilities to stimulate interaction between users. However, as mentioned above, research shows that the opportunity to interact on social media remains unexploited (Vergeer, Hermans & Sams, 2011). In addition, it appears that political websites are mostly used in the same manner as the traditional mass media, resulting in one-way communication, ignoring among other things the potential for interactivity and horizontal communication (Vergeer & Hermans, 2013). Also, the websites only reach users who actively search for them. Therefore, examples of good practice of online interaction by politicians are scarce, although many politicians claim that it is of great importance that governments listen and converse with citizens (Gurevitch, Coleman & Blumer, 2009). After all, a meaningful relationship between citizens and politicians is important, as citizens need to feel represented by politicians in order for a democratic government to be successful (Graham, Broersma, Hazelhoff & Van 't Haar, 2013).

Optimism regarding interaction on SNSs still exists, as Vergeer and Hermans (2013) show that the first signs of an increase in interactive behaviour were found in earlier studies. For example, Vaccari (2008) showed that in the 2004 US elections candidates used an email list with committed volunteers and supporters, which could be used to create a virtual community for virtual campaigning.

Another example comes from Foot, Schneider and Dougherty (2007) who show that the 2004 US congressional campaign of Howard Dean featured a network of websites that connected over 500 discussion groups, action coordinators, and supporters' websites, creating a huge community in which users could interact with each other. These examples of good practice might indicate that the interactive features of SNSs will be deployed more in the future.

Engaging in interaction would take a shift in the manner in which politicians broadcast their messages. Whereas politicians used to have control over the political agenda and be proactive, they are now forced to be more responsive (Gurevitch, Coleman & Blumler, 2009). These days, politicians need to adapt to the interactive audience by responding to their questions and challenging messages, redistribute messages, and modify received messages, while also appearing as a sincere and authentic person with whom citizens would want to interact (Gurevitch, Coleman & Blumler, 2009).

2.3.1 Benefits of interaction

Participating in the conversations on SNSs entails advantages for both politicians and citizens. First, by interacting with citizens, politicians keep citizens up to date and they give citizens attention. These are things that citizens desire from politicians, and therefore politicians might earn more votes if they fulfil this desire (Spierings & Jacobs, 2014). Second, if politicians would interact with citizens on social media platforms, this might lead to more transparency in political affairs, and involvement of citizens in processes of political decision-making (Stieglitz & Dang-Xuan, 2013). Furthermore, by using Twitter more actively and by engaging in interaction on Twitter, politicians can reach an interesting cohort of citizens; the digital natives (Moeller et al., 2014). This is the youngest cohort of voters and these voters use SNSs in large quantities. Therefore, it is easier to reach them via social media, whereas they are far more difficult to reach via the more traditional mass media (Moeller et al., 2014; Vergeer, Hermans & Sams, 2011). Reaching these younger citizens through a medium they are already using, could entice them into the political realm (Vergeer, Hermans & Sams, 2011). Even more so, according to Moeller et al. (2014), younger citizens develop their internal political efficacy by engaging in political discussions and by sharing information about politics. As politicians can obtain votes from younger citizens and younger citizens experience political efficacy from interaction between politician and citizens, interaction is a double-edged sword.

2.4 Aspects of interaction on Twitter

In order to determine what constitutes interaction, and what kind of messages evoke interaction, it is interesting to consider the content and the structure of these messages in depth. In their article on social media analytics in political communication, Stieglitz and Dang-Xuan (2013) describe three categories for content analysis of social media that can be applied individually or combined; the topic and issue category, the opinion and sentiment category, and the structural category. This section shows the aspects of interaction on the social medium Twitter using these three content categories.

2.4.1 Topic and issue category

The first content category from the work of Stieglitz and Dang-Xuan (2013) is the topic and issue category, which refers to the identification of the topic of a message. To get a clear view of the subject of a message, the content is determined by three variables; the topic of a tweet, possibly visual content, and tweet characteristics such as hashtags and @-mentions. Each of these aspects will be elaborated below.

Topic of a tweet

When studying political communication, it is possible to determine the presence of a political conversation by using a range of subjects. These subjects on the Internet and social media can be public as well as private (Shirky, 2011). Fernandes, Giurcanu, Bowers and Neely (2010) studied public content in their research. The subjects they used were based on Sweetser Trammell's (2007) study, which were *war*, *economy*, *security/defence, satisfaction* and *dissatisfaction with the government, international issues/foreign policy, education*, and *health care*. These topics partially overlap with the overview of the Dutch party programmes (Kamerbreed, n.d.). Kamerbreed (n.d.) added the topics *Europe*, *social affairs and employment*, *media and culture, integration,* and *citizen and governance*. Kamerbreed (n.d.) also contains a topic similar to *health care*, which is named *public health*, *welfare and sports*, and the topic *economy* includes taxes and other financial affairs.

There can also be private content on the Twitter accounts of politicians. Since Twitter provides users with the possibility to create their own content, and because politics have become more personalized, it is very likely that politicians also share content from their personal life on Twitter (Bennett, 2012). Sharing things from politicians' private lives is beneficial, in that it engages citizens in the lives of the politicians. In their research concerning celebrities on Twitter, Marwick and Boyd (2011) call this performative intimacy. Private content relates to topics addressed by politicians considering their life outside of the political arena. Aspects of personal life to consider are *family and friends, voluntary activities, religion, home,* and *leisure* (e.g. sports and hobbies) (Chalofsky & Cavallaro, 2013). Based on the argument by Marwick and Boyd (2011), it can be expected that Twitter users show a lot of interest in the more private tweets from politicians in the form of reactions, retweets, and likes.

Visual content

Users of Twitter are able to share 'visual content' alongside the 140-character messages. Pictures on Twitter are mostly related to everyday life, showing *food*, the *weather*, *street scenes*, and *events* (Kaneko & Yanai, 2013). In the context of political communication, such pictures would reveal things from the life of a politician. This could concern not only *formal publicity stills* and *campaign material*, but personal and candid pictures as well. Sharing personal pictures would even reinforce performative intimacy, offering citizens a glimpse into the personal life of the politician (Marwick & Boyd, 2012). Visual content offers Twitter users a richer view of the life of celebrities, such as politicians, and because users are interested in those lives (Marwick & Boyd, 2012), it can be expected that the addition of visual content to a tweet will lead to more interaction.

Tweet characteristics

On the social media platform Twitter, a user has several features available to engage in interaction and create connections. Zappavigna (2011) describes these features, calling them 'linguistic markers'. Zappavigna (2011, p. 790) writes that these features can be used "to bring other voices into tweets by addressing other users, republishing other tweets, and flagging topics that may be adopted by multiple users". The first refers to the *@-mention*, indicating that someone is addressed in the message by putting the username of the addressee behind the '@' symbol (Zappavigna, 2011). The second type of interaction can be achieved by redistributing a message of another user with a *retweet*. A tweet from a user will be shown on the feed of the user that retweets the message. A *retweet* can be recognized by the letters 'RT' in front of the tweet, and is often followed by a *@-mention* to indicate the source (Zappavigna, 2011). Finally, flagging topics can be done by using *hashtags*, which can be recognized by the '#' symbol (Zappavigna, 2011). With a *hashtag*, the user defines the topic of the tweet and creates a reference to other tweets with the same hashtag (Zappavigna, 2011). Finally, users can also add *URL's, emoticons*, and *polls* to their tweets. *Polls* invite other users to answer a multiple choice question. Based on this section, it can be expected that tweets with these features will bring about more interaction as compared to tweets that do not have these features.

2.4.2 Opinion and sentiment category

The second content category from Stieglitz and Dang-Xuan (2013) refers to the opinion and sentiment of a message. Users of social media can express, among other things, their points of view and feelings on social media. Users do so more than ever before, which is important, because people prefer to hear other opinions before they make their own decision (Stieglitz & Dang-Xuan, 2013). Within the opinion and sentiment category there are two important aspects to consider; the 'tone' of a message and the use of 'humour'.

Tone

In research, opinion sharing is translated into 'sentiment analysis' or 'opinion mining' (Stieglitz & Dang-Xuan, 2013). This method is named coding for 'tone', or understanding "the valence of sentiment" in Diakopoulos and Shamma's (2010, p. 1196) research. The codes for 'tone', that Diakopoulos and Shamma (2010) used in their study were *negative, positive, mixed* (positive as well as negative)*,* or *other* (non-evaluative content). Fernandes et al. (2010) considered tone in terms of *positive*, *negative*, an *equal mix of positive and negative*, or *neutral*. In their analysis of a sample of political news articles, De Vreese et al. (2006) coded 'tone of the news' using the codes *neutral* (non-evaluative content)*, negative, positive, dominantly negative, dominantly positive,* or *mixed.* Although computerized methods for analysing 'tone' have been greatly advanced, these methods still lack the ability to handle emoticons, acronyms, amplifications, slang, and sarcasm or irony in informal messages (Stieglitz & Dang-Xuan, 2013).

Humour

In addition to 'tone', it is important to take 'humour' into consideration when analysing the sentiment of tweets (Raz, 2012; Zhang & Liu, 2014). This is important, because besides affecting feelings, humour also has an influence on human beliefs (Raz, 2012). The aspect of influencing human beliefs is important in the political context, as political messages from politicians as well as citizens aim at convincing others of, for example, the verity of a particular viewpoint. On Twitter, humorous posts possess certain characteristics that plain tweets and humorous non-tweets do not (Raz, 2012; Zhang & Liu, 2014). Raz (2012) describes three theories of humour in order to recognize 'humour' in a tweet, the first being *incongruity humour* which refers to the presence of one statement with two contradictory interpretations as a condition for humour. The second is the *superiority theory* which involves feelings of victory or triumph over someone who is or something that is wrong, inferior, or defeated (Meyer, 2000; Raz, 2012). The third is the *relief humour* which refers to humour containing taboo and is described as "a license for banned thoughts" (Raz, 2012, p. 78). The humour releases physiological tension (Meyer, 2000). Based on the former paragraph, 'humour' in a tweet most likely leads to more interaction as it is convincing and appealing when used appropriately.

2.4.3 Structural category

The third and final content category for social media analytics is the structural category (Stieglitz & Dang-Xuan, 2013). This category regards the identification of influential users (i.e. opinion leaders) of social media (Stieglitz & Dang-Xuan, 2013). Politicians might (attempt to) interact with such actors, or mention them in their messages (Stieglitz & Dang-Xuan, 2013). Thus, the relevant aspect of the structural category is 'actors'.

Actors

As Zappavigna (2011) explained, Twitter users can use a @-mention to involve other users in a tweet. This type of Twitter behaviour can take place between many different actors (Dahlgren, 2005). For example, mentioning other users can take place between citizens, but also, between citizens and the media, or politicians (Dahlgren, 2005). In their analyses of news coverage during the 2004 European parliamentary elections, De Vreese, Banducci, Semetko and Boomgaarden (2006) identified stories about the elections based on a set of codes defining different 'types of actors'. In their research, an actor is a *person, groups of persons with a shared interest, an institution,* or *another organization* (De Vreese et al., 2006). It is interesting to investigate the 'actors' mentioned in a tweet, as some actors could generate more interaction than others. It might be expected that mentioning more influential Twitter users, such as other politicians, the media, or other opinion leaders, brings about more interaction than less influential users, such as citizens.

2.4.4 Additional content

Besides the three content categories that Stieglitz and Dang-Xuan (2013) describe, they also describe other aspects of a message that are interesting to take into account when executing an analysis of social media. This concerns an identification of the author of the message, and a time stamp. The following section shows two relevant aspects of a message; 'network characteristics' and 'candidate characteristics', and 'timing'.

Network and candidate characteristics

In their research on the use of Twitter by candidates of the Dutch general elections, Vergeer and Hermans (2013) took into account 'network characteristics' and 'candidate characteristics'. Doing so, contributes to the outlining of the interaction on Twitter based on individual candidates. Vergeer and Hermans (2013) measured 'network characteristics' by the network size*,* represented by the *amount of followers of a politician*, the *amount of people the politician follows*, and *reciprocal following*. A politician with more followers will most likely trigger more interaction with a tweet than a politician with fewer followers.

'Candidate characteristics' were measured by Vergeer and Hermans (2013) based on the prioritization of each candidate, meaning a *politicians' position* on the list of electoral candidates of a party. The prioritization shows the likelihood that a candidate will be elected, with a lower number representing a higher prioritization. It is expected that, without considering the *amount of followers*, electoral candidates with a similar *prioritization* will bring about comparable amounts of interaction with their tweets.

Timing

Before the Internet, politicians and political parties decided, in cooperation with the media, when a message from that politician or political party would be distributed (Mangold & Faulds, 2009). Besides face-to-face and word-of-mouth communication, the receivers of the communication expressions were not in control of when a certain topic was distributed (Mangold & Faulds, 2009). However, with the possibilities of the Internet, everyone can access, (re)distribute, and comment on content at any given moment (Mangold & Faulds, 2009). Therefore, it is interesting for a politician to know on which moment it is most likely that people will see, redistribute, or comment on messages from that politician (De Vries, Gensler & Leeflang, 2012). When a politician has that knowledge, he or she is in the position to post whenever he or she can expect the most reactions, retweets, and likes, thus increasing popularity (De Vries, Gensler & Leeflang, 2012). In other words, if a politician has good 'timing', the politician gains back some control over which topics are discussed at what moments. Based on the former paragraph it is expected that although users can access any public information on social media at any time, there will be moments during which a message will receive more response than messages sent at a different time.

2.5 Research goal

The former chapter offered insight in, among other things, the use of social media in political communication, the benefits and drawbacks of social media in political communication, the benefits of engaging in interaction, and which aspects of a message to consider when investigating interaction. In this study, the use of these aspects of interaction by Dutch list pullers will be investigated in order to determine which Twitter content triggers interaction in a political context.

3. Method

An already existing sample of Twitter messages from politicians was analysed by means of a content analysis. Content analysis is considered a straightforward method to go through substantial amounts of data, and is very helpful in attempts to find patterns and trends (Stemler, 2001). The analysed corpus was gathered using NodeXL.

3.1 Context

The Netherlands started as a frontrunner in the adoption of social medium Twitter with an adoption rate of 22.0% of the Dutch population in 2010 (Vollman, 2011), and 27.0% in 2011 (Graham, Jackson & Broersma, 2016; Vergeer & Hermans, 2013). The presence of such a large amount of Dutch citizens on Twitter led to the deployment of this micro-blogging service by many Dutch politicians. Today, in 2017, approximately 15.3% of the Dutch citizens have a Twitter account (Van der Veer, Boekee & Peters, 2017), which indicates a decrease in the adoption rate. However, all list pullers of the former Dutch House of Representatives (i.e. Second Chamber) as well as the list pullers of new parties present in the current House of Representatives still use Twitter as an important part of their campaigns.

3.2 Corpus

The corpus of the research contained the original tweets sent by the list pullers who used Twitter in their campaign during the most recent Dutch election period (N = 2158), which ran between December 19th, 2016 and March 23rd, 2017 (Tweede Kamer der Staten-Generaal, n.d.). An original tweet is the first tweet of a conversation, and therefore not a reaction to another tweet or a retweet. The elections determined which politicians and political parties would represent the Dutch people for the following four years (Kieswet 2001, art. C 1.1). An election period was chosen, since such a period is one of the most intensive with regard to communication and interaction between politicians and citizens (Graham, Jackson & Broersma, 2014). The selected list pullers for the research were all list pullers present in the former and the current House of Representatives (N = 13). Table 1 shows an overview of these list pullers, the party they are associated with, the number of tweets they sent during the election period, the amount of followers of each list puller, and the amount of users each list puller follows.

Table 1: *Overview of selected list pullers participating in the 2017 Dutch elections*

List puller	Twitter username	Political party	Political orientation[1]	Original tweets during election period	Followers[3]	Following users[3]
Sybrand Buma	@sybrandbuma	CDA	Centre right, conservative	31	70106	326
Tunahan Kuzu	@tunahankuzu	DENK	Left, progressive	44	29152	68
Emile Roemer	@emileroemer	SP	Left, progressive	54	175393	725
Mark Rutte	@MinPres	VVD	Right, conservative	56	797875	0
Jesse Klaver	@jesseklaver	GL	Centre left, progressive	58	89327	524
Alexander Pechtold	@APechtold	D66	Centre, progressive	90	630168	595
Kees van der Staaij	@keesvdstaaij	SGP	Centre right, conservative	96	51975	1787
Marianne Thieme	@mariannethieme	PvdD	Left, progressive	145	71746	3454
Gert-Jan Segers	@gertjansegers	CU	Centre	209	22742	495
Lodewijk Asscher	@LodewijkA	PvdA	Centre left, progressive	212	225744	1398
Henk Krol	@HenkKrol	50PLUS	Left	294	15488	218
Thierry Baudet	@thierrybaudet	FvD	-	407	40556	193
Geert Wilders	@geertwilderspvv	PVV	Centre right, conservative	462[2]	829760	1

[1] From Kieskompas (2017)
[2] For Geert Wilders, all English tweets that were direct translations of a Dutch tweet were deleted from the corpus
[3] Numbers were retrieved on June 21st, 2017

3.3 Codebook

The codebook was constituted following the deductive approach, meaning that it was determined before the actual coding began (Semetko & Valkenburg, 2000; White & Marsh, 2006). This is beneficial, as the deductive approach is easy to replicate and is applicable to large samples (Semetko & Valkenburg, 2000). The first codes of the codebook (Appendix A) are typical data to code, namely the 'ID of a post', the 'timing' of the post, and a reference to the author in the form of the 'network characteristics' and 'candidate characteristics' (Stieglitz & Dang-Xuan, 2013). The codebook is based on the three content categories from the work of Stieglitz and Dang-Xuan (2013) described in the theoretical framework. In their research, they describe a guideline for developing toolsets and codebooks for the analysis of social media in a political context (Stieglitz & Dang-Xuan, 2013). The following two sections show the interaction variables of the research based on the features of Twitter, and the independent variables falling under the three content categories.

3.3.1 Interaction variables

The interaction variables apply particularly to the features of Twitter. The dependent variables of this research were the interaction variables shown in Table 2; amount of *reactions* (number of reactions following the original tweet), amount of *retweets* (number of times the original tweet was redistributed), and amount of *likes* (number of likes for the original tweet).

Table 2: *Frequencies of interaction variables in corpus*

Dependent variable	Minimum	Maximum	Mean	Median	Std. deviation
Amount of reactions	0	1471	47.30	13.50	103.807
Amount of retweets	0	5823	142.95	34.00	340.329
Amount of likes	0	9536	246.97	52.00	554.945

3.3.2 Independent variables

The following elaborates upon the independent variables of the codebook. Each of those variables is a code in the codebook which falls under the three content categories from Stieglitz and Dang-Xuan (2013); the topic and issue category, the opinion and sentiment category, and the structural category.

Topic and issue category

The topic and issue category refers to the content of an original tweet sent by a list puller. First, the 'topic of a tweet' was coded by choosing the most relevant and prominent topic from a list of topics based on literature (e.g. *war/terrorism*, *education*, *health care*). Additional topics were *campaign activities*, because the tweets were sent during the election period, and *celebration* for national holidays that took place during that same period, and *other*. Finally, for tweets that addressed more than one topic without one of them standing out the most, the code *multiple topics* was used. Second, when a tweet contained 'visual content' (e.g. *formal publicity*, *street scenes, events*) it was also coded for the most relevant and prominent subject. If a tweet did not contain any visual content, it was coded *not applicable*. Third, besides a topic and visual content, other 'tweet characteristics' could be *hashtags* (#), *@-mentions*, *polls*, *emoticons,* and *URL's*, which were coded using no (0) or yes (1).

Opinion and sentiment category

To represent the opinion and sentiment category, this research measured opinion and sentiment by coding for 'tone' of a tweet (*negative, non-evaluative, positive*, and *mixed*) and the presence of 'humour' (*no* or *yes*) in a tweet. 'Tone' indicated the emotional valence of a tweet. A tweet was coded as *negative* if it showed emotions such as sadness, anger, and confusion, whereas *positive* tweets showed happiness, satisfaction, excitement, or curiosity. *Non-evaluative* tweets were neutral and showed none of these emotions. A tweet was coded as *mixed* if both positive as well as negative emotion was present in a tweet. Also, the use of emoticons could reinforce the emotional valence of a tweet, which was useful for indicating the 'tone'. 'Humour' was coded as present when a tweet contained, for example, jokes, wordplay, sarcasm, or irony. A winking emoticon could indicate use of 'humour' as well, and therefore extra attention was paid to tweets containing a winking emoticon.

Structural category

The structural category was applied by coding the 'actors' (e.g. a *citizen*, a *politician*, *media*) mentioned by the politicians in their original tweet by using a @-mention. In order to find out which type of actor a mentioned user was, coders first looked at the user's profile, and if it was necessary to the URL in the user's account description.

3.4 Validity and reliability

In order to ensure the codebook's validity, it contained categories that were relevant in answering the research question and that only measured the intended concept (Stemler, 2001; White & Marsh, 2006). Thus, categories had to be mutually exclusive, meaning that data could not fall between two categories and all data was represented by only one category, and exhaustive, meaning that all important aspects of a category are represented in the data (Stemler, 2001; White & Marsh, 2006).

To ensure the reliability and reproducibility of this study, it was important that all coders would code the same item in the same manner. Because the research applied the deductive approach, it was possible to pre-test the codebook to control for the coding behaviour of the researcher, and thus ensuring the reliability of the research. The pre-test was executed by appointing a second coder to code a random selection of 10.2% (N = 221) of the corpus using the codebook. The researcher coded the same selection. After coding the tweets, the codes of the second coder were compared to the codes of the researcher, or first coder, using Cohen's Kappa. With an average inter-coder agreement of .7, it was sufficiently reliable. Only one pre-test was executed. The Kappa's from the pre-test are shown in Table 3, and the separate Kappa's for each actor are shown in Appendix B.

Table 3: *Results pre-test*

	Code	Initial Kappa	Sig.	Confidence interval
Interaction variables	Reactions	0.866	p < .005	95%
	Retweets	0.917	p < .005	95%
	Likes	0.881	p < .005	95%
Topic and issue category	Topic of the tweet	0.503	p < .005	95%
	Visual content	0.738	p < .005	95%
	Emoticon	0.829	p < .005	95%
	Hashtag	0.929	p < .005	95%
	@-mention	0.932	p < .005	95%
	Poll[1]	-	-	-
	URL	0.753	p < .005	95%
Opinion and sentiment category	Tone	0.373	p < .005	95%
	Humour	-0.025	p = .705	95%
Structural category	Actors (mean)	0.687	p < .005	95%

[1] Not present in pre-test

Based on the first and only pre-test of this research, not all individual codes were reliable because the Kappa's were not high enough. This was true for three of the fifteen codes for 'actors'; *politician sender's party* (k = 0.534, 95% CI, p < .005), *interest group* (k = -0.006, 95% CI, p = .924), and *other* actors (k = 0.349, 95%, p < .005), and to the codes 'tone' and 'humour'.

Codes with an insufficient Kappa were adapted or the descriptions in the codebook were improved in accordance with consultation with the second coder. This resulted in more examples of actors in the description of the codes for 'actors', and to more examples of what types of humour a humorous tweet could contain. The code 'tone' was adapted to be more unambiguous by removing the vaguer codes *slightly negative* and *slightly positive*. Finally, based on the pre-test it became evident that the codes for 'visual content' and codes for 'topic of the tweet' were not exhaustive. Therefore *text and media* was added to the code 'visual content', and the categories *environment*, *animals*, and *public transportation/infrastructure* were added to the code 'topic of the tweet'.

3.5 Data analysis

The unit of coding consists of one individual tweet. This refers to each original tweet sent by a list puller from the former and current House of Representatives during the Dutch elections of 2017. Coding and analysis were performed using the statistics programme SPSS. In order to determine which content from the list pullers was followed by a significantly large amount of interaction, a median split of the interaction variables was performed. Using a median split facilitates the interpretation of the results. This split divided the interaction variables, creating a part with low interaction and a part with high interaction. This resulted in an approximately equal distribution of the interaction variables ‘reactions’ (low = 1115, high = 1043), ‘retweets’ (low = 1086, high = 1072), and ‘likes’ (low = 1091, high = 1067) as shown in Table 4.

Table 4: *Median split of interaction variables*

	Reactions		Retweets		Likes	
	Frequency	Percentage	Frequency	Percentage	Frequency	Percentage
Low	1115	51.7	1086	50.3	1091	50.6
High	1043	48.3	1072	49.7	1067	49.4
Total	2158	100.0	2158	100.0	2158	100.0

The split variables were used in cross tables and Chi²-tests to determine if an independent variable triggered significantly less or more ‘reactions’, ‘retweets’, and ‘likes’. The residuals in the cross tables showed a significant effect if those numbers were higher of lower than 2 (Lammers, Pelzer, Hendrickx & Eisinga, 2007).

4. Results

In total, 2158 original tweets from 13 list pullers seated in the former and/or current Dutch House of Representatives were analysed using the codebook (Appendix A). It was first investigated if the interaction variables ‘reactions’, ‘retweets’, and ‘likes’ correlated with each other. If they do, it means that when one interaction variable is high or low, it is very likely that the other interaction variables are high or low as well. As can be seen in Table 5, the interaction variables correlate with each other on a moderate to high level.

Table 5: *Correlation between interaction variables*

		Reactions	Retweets
Reactions	Pearson Correlation	1	-
	Sig. (2-tailed)	-	-
Retweets	Pearson Correlation	0.736	1
	Sig. (2-tailed)	< .001	-
Likes	Pearson Correlation	0.768	0.895
	Sig. (2-tailed)	< .001	< .001

The results will be presented in the sections below, following the three content categories of Stieglitz and Dang-Xuan (2013). The chapter closes with the results of the codes ‘network characteristics’ and ‘candidate characteristics’, and ‘timing’.

4.1 Topic and issue category

The topic and issue category is represented by the independent variables ‘topic of a tweet’, the ‘visual content’ that is possibly added to a tweet, and the ‘tweet characteristics’ in the form of emoticons, *hashtags, @-mentions, polls,* and *URL’s*.

4.1.1 Topic of the tweet

With regard to the ‘topic of the tweet’, Figure 1 shows that during the election period, list pullers mostly sent out tweets with regard to their *campaign activities* (N = 702).

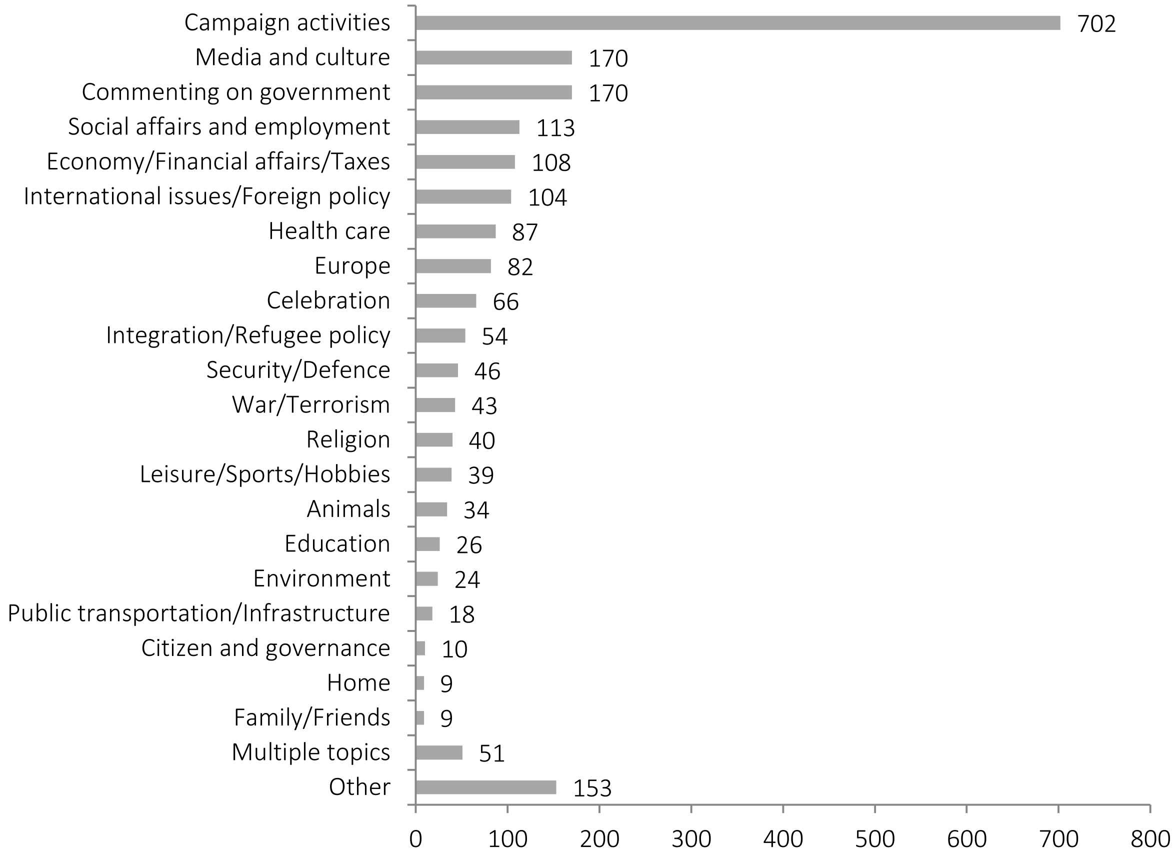

Figure 1: *Frequencies of topic of the tweet*

Besides campaign activities, other popular topics were *media and culture* (N = 170), *commenting on the government* and other politicians (N = 170), and *social affairs and employment* (N = 113). Public subjects that were mentioned the least often were *environment* (N = 24), *public transportation/infrastructure* (N = 18), and *citizen and governance* (N = 10). Tweets considered mostly public content. For example, topics such as *leisure/sports/hobbies* (N = 39), *home* (N = 9), and *family/friends* (N = 9) have relatively low frequencies as compared to most public topics.

A Chi²-test was executed to find significant differences in the amount of interaction triggered by the topic of a tweet. These differences were found for 'reactions' ($\chi^2(22, N = 2158) = 202.008$, $p < .001$), for 'retweets' ($\chi^2(22, N = 2158) = 221.705$, $p < .001$), and for 'likes' ($\chi^2(22, N = 2158) = 245.940$, $p < .001$). The residuals showed that the topics that triggered significantly more reactions, retweets and likes were *war/terrorism*, *comments on government*, *international issues/foreign policy, Europe, integration/refugee policy, religion*, and tweets with *multiple topics*. Topics that resulted in significantly fewer reactions, retweets and likes were *economy/financial affairs/taxes, health care, social affairs and employment, media and culture*, and *public transportation/infrastructure*. The topic *campaign activities* led to significantly fewer reactions and retweets (Table 6).

Table 6: *Amount of interaction for topic of the tweet*

		Reactions		Retweets		Likes	
		Low	High	Low	High	Low	High
War/terrorism	Count	11	32	8	35	12	31
	Adj. Residual	**-3.5**	**3.5**	**-4.2**	**4.2**	**-3.0**	**3.0**
Economy/financial affairs/taxes	Count	73	35	71	37	86	22
	Adj. Residual	**3.4**	**-3.4**	**3.3**	**-3.3**	**6.2**	**-6.2**
Security/defence	Count	22	24	16	30	18	28
	Adj. Residual	-0.5	0.5	-2.1	2.1	-1.6	1.6
Commenting on government	Count	57	113	58	112	61	109
	Adj. Residual	**-4.9**	**4.9**	**-4.4**	**4.4**	**-4.0**	**4.0**
International issues /foreign policy	Count	23	81	26	78	27	77
	Adj. Residual	**-6.2**	**6.2**	**-5.3**	**5.3**	**-5.1**	**5.1**
Education	Count	17	9	14	12	18	8
	Adj. Residual	1.4	-1.4	0.4	-0.4	1.9	-1.9
Health care	Count	68	19	59	28	62	25
	Adj. Residual	**5.0**	**-5.0**	**3.3**	**-3.3**	**3.9**	**-3.9**
Europe	Count	31	51	23	59	28	54
	Adj. Residual	**-2.6**	**2.6**	**-4.1**	**4.1**	**-3.0**	**3.0**
Social affairs and employment	Count	71	42	81	32	95	18
	Adj. Residual	**2.4**	**-2.4**	**4.7**	**-4.7**	**7.3**	**-7.3**
Media and culture	Count	105	65	110	60	103	67
	Adj. Residual	**2.7**	**-2.7**	**3.9**	**-3.9**	**2.7**	**-2.7**
Integration/refugee policy	Count	14	40	8	46	13	41
	Adj. Residual	**-3.8**	**3.8**	**-5.3**	**5.3**	**-3.9**	**3.9**
Citizen and governance	Count	2	8	4	6	4	6
	Adj. Residual	**-2.0**	**2.0**	-0.7	0.7	-0.7	0.7
Environment	Count	17	7	11	13	16	8
	Adj. Residual	1.9	-1.9	-0.4	0.4	1.6	-1.6
Animals	Count	26	8	17	17	23	11
	Adj. Residual	**2.9**	**-2.9**	0.0	0.0	**2.0**	**-2.0**
Public transportation /infrastructure	Count	15	3	15	3	16	2
	Adj. Residual	**2.7**	**-2.7**	**2.8**	**-2.8**	**3.3**	**-3.3**
Campaign activities	Count	396	306	384	318	359	343
	Adj. Residual	**3.1**	**-3.1**	**2.8**	**-2.8**	0.4	-0.4
Family/friends	Count	6	3	5	4	2	7
	Adj. Residual	0.9	-0.9	0.3	-0.3	-1.7	1.7
Religion	Count	11	29	9	31	12	28
	Adj. Residual	**-3.1**	**3.1**	**-3.6**	**3.6**	**-2.6**	**2.6**
Home	Count	3	6	4	5	3	6
	Adj. Residual	-1.1	1.1	-0.4	-0.4	-1.0	1.0
Leisure/sports/hobbies	Count	21	18	27	12	18	21
	Adj. Residual	0.3	-0.3	**2.4**	**-2.4**	-0.6	0.6
Celebration	Count	31	35	36	30	25	41

	Adj. Residual	-0.8	0.8	0.7	-0.7	-2.1	2.1
Multiple topics	Count	11	40	10	41	8	43
	Adj. Residual	**-4.4**	**4.4**	**-4.4**	**4.4**	**-5.0**	**5.0**
Other	Count	84	69	90	63	81	71
	Adj. Residual	0.8	-0.8	**2.2**	**-2.2**	0.8	-0.8

4.1.2 Visual content

It appears from Figure 2 that the 'visual content' that was used the most by list pullers were pictures intended for *formal publicity* (N = 217), pictures showing *corporate visual identity* (N = 191), and *text or pieces from the media* (N = 190). List pullers did not often share images of *events* (N = 44), *street scenes* (N = 38), the *weather* (N = 38), or *food* (N = 3).

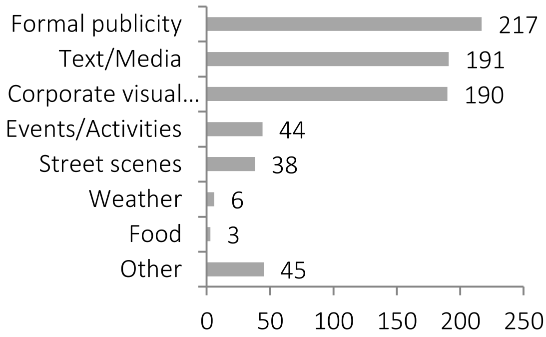

Figure 2: *Frequencies of visual content*

A Chi²-test showed that there were some significant differences with regard to the interaction triggered by the addition of visual content to a tweet ('reactions', $\chi^2(8, N = 2158) = 31.151$, $p < .001$, 'retweets', $\chi^2(8, N = 2158) = 47.050$, $p < .001$, 'likes', $\chi^2(8, N = 2158) = 69.321$, $p < .001$). The residuals show that not adding visual content led to significantly less interaction, and visual content containing *corporate visual identity* or *other* visual content triggered significantly more reactions, retweets and likes (Table 7).

Table 7: *Results for use of visual content in a tweet*

		Reactions		Retweets		Likes	
		Low	High	Low	High	Low	High
No visual content	Count	769	655	740	684	789	635
	Adj. Residual	**3.0**	**-3.0**	**2.1**	**-2.1**	**6.3**	**-6.3**
Formal publicity	Count	100	117	113	104	89	128
	Adj. Residual	-1.7	1.7	0.5	-0.5	**-3.0**	**3.0**
Corporate visual identity	Count	75	115	70	120	60	130
	Adj. Residual	**-3.5**	**3.5**	**-3.9**	**3.9**	**-5.5**	**5.5**
Food	Count	2	1	2	1	1	2
	Adj. Residual	0.5	-0.5	0.6	-0.6	-0.6	0.6
Weather	Count	4	2	5	1	4	2
	Adj. Residual	0.7	-0.7	1.6	-1.6	0.8	-0.8
Street scenes	Count	24	14	24	14	23	15
	Adj. Residual	1.4	-1.4	1.6	-1.6	1.2	-1.2
Events/activities	Count	29	15	33	11	25	19
	Adj. Residual	1.9	-1.9	**3.3**	**-3.3**	0.8	-0.8

Text/media	Count	98	93	89	102	91	100
	Adj. Residual	-0.1	0.1	-1.1	1.1	-0.8	0.8
Other	Count	14	31	10	35	9	36
	Adj. Residual	**-2.8**	**2.8**	**3.8**	**-3.8**	**-4.1**	**4.1**

4.1.3 Tweet characteristics

The frequencies of the 'tweet characteristics' are shown in Figure 3. *Polls* (*N* = 2) and *emoticons* (*N* = 88) were not used as much as other features. *Hashtags* (*N* = 757) and *@-mentions* (*N* = 580) were used more frequently. The feature that was applied the most was the addition of one or more *URL's* to a tweet (*N* = 1243).

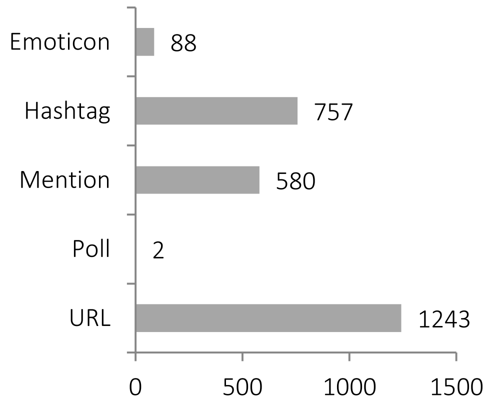

Figure 3: *Frequencies of tweet characteristics*

A Chi²-test to the cross tables of the split interaction variables determined which tweet characteristics resulted in a significantly higher or lower amount of interaction, as shown in Table 8.

Table 8: *Results of use of tweet characteristics in a tweet*

		Reactions		Retweets		Likes	
		Low	High	Low	High	Low	High
Emoticon	χ^2-value	4.253	4.253	1.548	1.548	12.886	12.886
	p-value	.039	.039	.213	.213	< .001	< .001
	Count	36	52	50	38	28	60
	Adj. Residual	**-2.1**	**2.1**	1.2	-1.2	**-3.6**	**3.6**
Hashtag	χ^2-value	0.139	0.139	11.726	11.726	20.114	20.114
	p-value	.709	.709	.001	.001	< .001	< .001
	Count	387	370	343	414	333	424
	Adj. Residual	-0.4	0.4	**-3.4**	**3.4**	**-4.5**	**4.5**
@-Mention	χ^2-value	26.848	26.848	18.359	18.359	6.266	6.266
	p-value	< .001	< .001	< .001	< .001	.012	.012
	Count	353	227	336	244	319	261
	Adj. Residual	**5.2**	**-5.2**	**4.3**	**-4.3**	**2.5**	**-2.5**
Poll	χ^2-value	-	-	-	-	-	-
	p-value[1]	1.000	1.000	1.000	1.000	.500	.500
	Count	1	1	1	1	2	0
	Adj. Residual	0.0	0.0	0.0	0.0	1.4	-1.4
URL	χ^2-value	61.222	61.222	22.518	22.518	94.517	94.517
	p-value	< .001	< .001	< .001	< .001	< .001	< .001
	Count	732	511	680	563	740	503
	Adj. Residual	**7.8**	**-7.8**	**4.7**	**-4.7**	**9.7**	**-9.7**

[1] Fisher's Exact test was applied as more than 25% of the expected counts were lower than 5 and/or the minimum count was lower than 1

Using a *hashtag* in a tweet led to a significantly larger amount of retweets and likes. As opposed to adding a hashtag to a tweet, using a *@-mention* in a tweet led to significantly less interaction in the form of reactions, retweets, and likes. If a list puller used an *emoticon* in a tweet, this led to significantly more interaction in the form of reactions and likes. There is no significant difference for the amount of retweets. As Figure 3 showed, list pullers added *URL's* to their tweets very often. However, adding these *URL's* resulted in a significantly smaller amount of interaction.

4.2 Opinion and sentiment category

The opinion and sentiment category is represented by the codes 'tone' and 'humour'. The following shows the results for both codes.

4.2.1 Tone

The 'tone' of a tweet was measured using the codes one through four. These codes represented respectively the tone *negative* (21.3%), *non-evaluative* (41.3%), *positive* (33.1%), and *mixed* (4.3%) for tweets with a tone that was positive as well as negative. Figure 4 shows the frequencies for each tone.

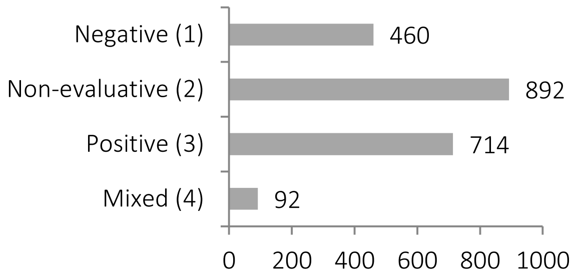

Figure 4: *Frequencies for tone*

An independent samples t-test was conducted to compare low and high amount of reactions, retweets, and likes to tone. The group statistics for tone (Table 9) show that tweets with a high amount of interaction in the form of reactions, retweets, and likes appear to be more neutral or negative rather than positive. In Table 10 it can be seen that these differences in tone are significant.

Table 9: *Group statistics of tone*

		N[1]	Mean	Std. Deviation
Reactions	Low	1085	2.24	0.669
	High	981	1.99	0.800
Retweets	Low	1060	2.26	0.647
	High	1006	1.98	0.810
Likes	Low	1062	2.18	0.657
	High	1004	2.06	0.823

[1] Tweets with the tone 'Mixed' were left out of the t-test

Table 10: *Independent samples t-test of tone*

	t	df	Sig. (2-tailed)
Reactions	7.539	2064	< .001
Retweets	8.652	2064	< .001
Likes	3.467	2064	.001

4.2.2 Humour

In addition to 'tone', 'humour' was measured as well. In the corpus, 'humour' was present 73 times. If a list puller used humour in a tweet, the candidate triggered significantly more interaction in the form of likes. The Chi²-test in Table 11 showed that there were only significant results for the code 'humour' when it concerned the amount of likes.

Table 11: *Results of use of humour in a tweet*

		Reactions		Retweets		Likes	
		Low	High	Low	High	Low	High
Humour	χ^2-value	0.296	0.296	0.291	0.291	6.746	6.747
	p-value	.587	.587	.590	.590	.009	.009
	Count	40	33	39	34	26	47
	Adj. Residual	0.5	-0.5	0.5	-0.5	-2.6	2.6

4.3 Structural category

The final content category from Stieglitz and Dang-Xuan's (2013) work is the structural category represented by the 'actors' that were mentioned in a tweet using a @-mention.

4.3.1 Actors

As could be seen in Figure 3, the corpus contained 580 tweets with one or more @-mentions. In total, there were 667 @-mentions, mentioning different actors. As shown in Figure 5, actors that were mentioned most often were politicians from the *list pullers' own party* (*N* = 85), the *list pullers' own party itself* (*N* = 133), and the *media* (*N* = 261). In ratio, these actors were mentioned in respectively 3.9%, 6.2%, and 12.1% of the whole corpus.

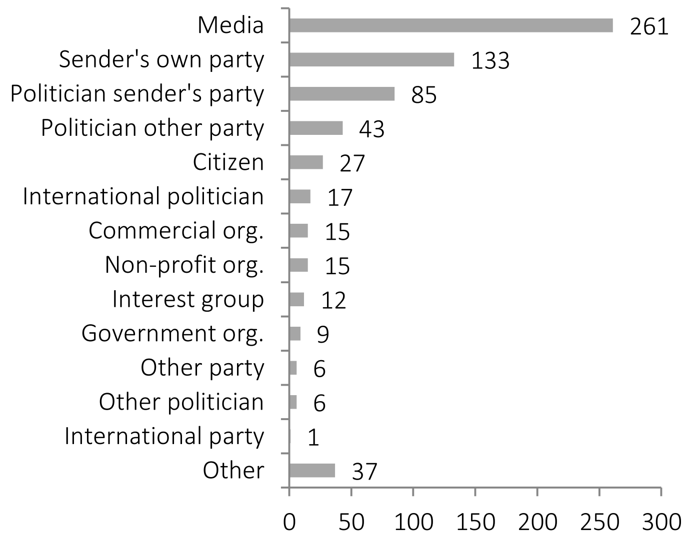

Figure 5: *Frequencies of mentioned actors*

With the use of a Chi²-test it was possible to determine if mentioning particular actors in a tweet led to more interaction. As Table 12 shows, significantly more interaction only occurred for mentioning an *international politician*.

Table 12: *Results for actors mentioned in a tweet*

		Reactions		Retweets		Likes	
		Low	High	Low	High	Low	High
Citizen	χ²-value	7.464	7.464	8.243	8.243	10.461	10.461
	p-value	.006	.006	.004	.004	.001	.001
	Count	21	6	21	6	22	5
	Adj. Residual	**2.7**	**-2.7**	**2.9**	**-2.9**	**3.2**	**-3.2**
Politician sender's party	χ²-value	17.858	17.858	6.172	6.172	2.420	2.420
	p-value	< .001	< .001	.013	.013	.120	.120
	Count	63	22	54	31	50	35
	Adj. Residual	**4.2**	**-4.2**	**2.5**	**-2.5**	1.6	-1.6
Politician other party	χ²-value	1.690	1.690	0.255	0.255	1.327	1.327
	p-value	.194	.194	.613	.613	.249	.249
	Count	18	25	20	23	18	25
	Adj. Residual	-1.3	1.3	-0.5	0.5	-1.2	1.2
Sender's own party	χ²-value	22.162	22.162	6.344	6.344	6.069	6.069
	p-value	< .001	< .001	.012	.012	.014	.014
	Count	95	38	81	52	81	52
	Adj. Residual	**4.7**	**-4.7**	**2.5**	**-2.5**	**2.5**	**-2.5**
Other party	χ²-value	-	-	-	-	-	-
	p-value[1]	.113	.113	.122	.122	.121	.121
	Count	1	5	1	5	1	5
	Adj. Residual	1.7	-1.7	1.7	-1.7	1.7	-1.7
Other politician	χ²-value	-	-	-	-	-	-
	p-value[1]	.438	.438	1.000	1.000	1.000	1.000
	Count	2	4	3	3	3	3
	Adj. Residual	-0.9	0.9	0.0	0.0	0.0	0.0
International politician	χ²-value	14.384	14.384	4.921	4.921	7.424	7.424
	p-value	< .001	< .001	.027	.027	.006	.006
	Count	1	16	4	13	3	14
	Adj. Residual	**-3.8**	**3.8**	**-2.2**	**2.2**	**-2.7**	**2.7**
International party	χ²-value	-	-	-	-	-	-
	p-value[1]	.483	.483	.497	.497	.494	.494
	Count	0	1	0	1	0	1
	Adj. Residual	-1.0	1.0	-1.0	1.0	-1.0	1.0
Media	χ²-value	8.560	8.560	9.755	9.755	5.068	5.068
	p-value	.003	.003	.002	.002	.024	.024
	Count	157	104	155	106	149	112
	Adj. Residual	**2.9**	**-2.9**	**3.1**	**-3.1**	**2.3**	**-2.3**
Government organization	χ²-value	-	-	-	-	-	-
	p-value[1]	.329	.329	.107	.107	.338	.338
	Count	3	6	2	7	3	6
	Adj. Residual	-1.1	1.1	-1.7	1.7	-1.0	1.0
Non-profit organization	χ²-value	1.361	1.361	1.614	1.614	0.539	0.539

	p-value	.243	.243	0204	.204	.463	.463
	Count	10	5	10	5	9	6
	Adj. Residual	1.2	-1.2	1.3	-1.3	0.7	-0.7
Commercial organization	χ^2-value	0.151	0.151	0.055	0.055	0.091	0.091
	p-value	.697	.697	.815	.815	.762	.762
	Count	7	8	8	7	7	8
	Adj. Residual	-0.4	0.4	0.2	-0.2	-0.3	0.3
Interest group	χ^2-value	2.631	2.631	5.260	5.260	5.186	5.186
	p-value	.105	.105	.022	.022	.023	.023
	Count	9	3	10	2	10	2
	Adj. Residual	1.6	-1.6	**2.3**	**-2.3**	**2.3**	**-2.3**
Other	χ^2-value	2.625	2.625	7.725	7.725	0.184	0.184
	p-value	.105	.105	.005	.005	.668	.668
	Count	24	13	27	10	20	17
	Adj. Residual	1.6	-1.6	**2.8**	**-2.8**	0.4	-0.4

[1] Fisher's Exact test was applied as more than 25% of the expected counts were lower than 5 and/or the minimum count was lower than 1

Mentioning some actors led to significantly less interaction. This was true for mentioning *citizens*, and for mentioning *politicians from the sender's party* with regard to reactions and retweets. Mentioning the Twitter-account of the *party a list puller is associated with* led to a significantly lower amount of reactions, retweets, and likes. When the *media* or *interest groups* were mentioned, the tweet triggered significantly less interaction as well.

4.4 Additional content

This section contains the results of the codes 'network characteristics', 'candidate characteristics', and 'timing'. To facilitate the interpretation of the results of 'timing', the code was divided into the week of the election, the day of the week, and the hour of the day.

4.4.1 Network and candidate characteristics

The *amount of followers* of list pullers is not equal for all list pullers. The list pullers from *D66*, *PVV*, and *VVD* have the most followers, whereas list pullers from *50PLUS*, *CU*, and *DENK* have the least. These frequencies were shown already in Table 1 in the method. When measuring differences in the interaction each list puller triggers, it is necessary to take these differences in amounts of followers into account, because when a Twitter user has more followers it can be expected that the user will also trigger more interaction on the messages he or she sends. Therefore, the variable *amount of followers* was weighted to prevent bias in further analysis. After that, a Chi²-test for 'candidate characteristics' was executed, which is shown in Table 13.

Table 13: *Results for candidate characteristics weighted for followers*

		Reactions		Retweets		Likes	
		Low	High	Low	High	Low	High
50PLUS	Count	4274688	278784	4383104	170368	4429568	123094
	Adj. Residual	**4743.3**	**-4743.3**	**4077.4**	**-4077.4**	**4593.0**	**-4593.0**
CDA	Count	911378	1261908	1191802	981484	1332014	841272
	Adj. Residual	**1118.4**	**-1118.4**	**1283.3**	**-1283.3**	**1748.7**	**-1748.7**
CU	Count	4116302	636776	3706946	1046132	3888882	864196
	Adj. Residual	**4400.3**	**-4400.3**	**3167.8**	**-3167.8**	**3790.5**	**-3790.5**
D66	Count	11973192	44741928	29617896	27097224	14493864	42221256
	Adj. Residual	**1370.8**	**-1370.8**	**6364.0**	**-6364.0**	**1826.9**	**-1826.9**
DENK	Count	320672	962016	583040	699648	437280	845408
	Adj. Residual	**319.9**	**-319.9**	**719.4**	**-719.4**	**519.7**	**-519.7**
FvD	Count	11680128	4826164	9125100	7381192	9084544	7421748
	Adj. Residual	**6452.3**	**-6452.3**	**3626.1**	**-3626.1**	**4191.4**	**-4191.4**
GL	Count	178654	5002312	178654	5002312	89327	5091639
	Adj. Residual	**-737.0**	**737.0**	**-948.0**	**948.0**	**-926.2**	**926.2**
PvdA	Count	25283328	22574400	33184368	14673360	36344784	11512944
	Adj. Residual	**7669.3**	**-7669.3**	**8883.2**	**-8883.2**	**11364.4**	**-11364.4**
PvdD	Count	8394282	2008888	5883172	4519998	6887616	3515554
	Adj. Residual	**6001.7**	**-6001.7**	**2966.7**	**-2966.7**	**4279.7**	**-4279.7**
PVV	Count	10786880	372562240	829760	382519360	829760	382519360
	Adj. Residual	**-11220.3**	**11220.3**	**-16339.5**	**16339.5**	**-14689.2**	**14689.2**
SGP	Count	3274425	1715175	2806650	2182950	2806650	2182950
	Adj. Residual	**3189.3**	**-3189.3**	**2028.2**	**-2028.2**	**2354.4**	**-2354.4**
SP	Count	2455502	7015720	2455502	7015720	3507860	5963362
	Adj. Residual	**956.0**	**-956.0**	**455.3**	**-455.3**	**1665.9**	**-1665.9**
VVD	Count	4787250	39893750	24734125	19946875	15957500	28723500
	Adj. Residual	**-824.2**	**824.2**	**6130.5**	**-6130.5**	**3487.7**	**-3487.7**

The Chi²-test showed that the differences were significant for 'reactions' ($\chi^2(12, N = 591916742) = 231014456, p < .001$), 'retweets' ($\chi^2(12, N = 591916742) = 293182423, p < .001$), and 'likes' ($\chi^2(12, N = 591916742) = 291652161, p < .001$). List pullers that triggered significantly more interaction were from *GL* and *PVV* according to the residuals. The residuals also showed that the list puller from *VVD* only triggered more reactions, and that the list pullers from all other parties triggered significantly less interaction in the form of reactions, retweets, and likes.

Another Chi²-test was executed to determine if there were any significant differences between the amount of interaction that a tweet triggered and the party a list puller is associated with when these results were weighted for the 'topic of the tweet'. The cross table for this Chi²-test is shown in Table 14.

Table 14: *Results for candidate characteristics weighted for topic of the tweet*

		Reactions		Retweets		Likes	
		Low	High	Low	High	Low	High
50PLUS	Count	3529	150	3601	78	3580	99
	Adj. Residual	**56.6**	**-56.6**	**59.8**	**-59.8**	**62.2**	**-62.2**
CDA	Count	171	195	211	155	237	129
	Adj. Residual	**-2.3**	**2.3**	**2.1**	**-2.1**	**5.8**	**-5.8**
CU	Count	2406	302	2228	480	2246	462
	Adj. Residual	**39.8**	**-39.8**	**33.1**	**-33.1**	**36.5**	**-36.5**
D66	Count	258	891	660	489	332	817
	Adj. Residual	**-21.0**	**21.0**	**3.7**	**-3.7**	**-14.5**	**14.5**
DENK	Count	178	433	321	290	212	399
	Adj. Residual	**-11.8**	**11.8**	0.2	-0.2	**-7.5**	**7.5**
FvD	Count	3306	1353	2757	1902	2550	2109
	Adj. Residual	**27.5**	**-27.5**	**10.6**	**-10.6**	**7.5**	**-7.5**
GL	Count	29	696	32	693	16	709
	Adj. Residual	**-26.6**	**26.6**	**-26.1**	**26.1**	**-26.0**	**26.0**
PvdA	Count	1500	1161	1902	759	1960	701
	Adj. Residual	**4.0**	**-4.0**	**21.0**	**-21.0**	**26.0**	**-26.0**
PvdD	Count	1450	333	1024	759	1114	669
	Adj. Residual	**25.1**	**-25.1**	**4.6**	**-4.6**	**11.1**	**-11.1**
PVV	Count	200	5919	16	6103	16	6103
	Adj. Residual	**-88.2**	**88.2**	**-92.6**	**92.6**	**-88.2**	**88.2**
SGP	Count	665	377	614	428	574	468
	Adj. Residual	**7.3**	**-7.3**	**4.5**	**-4.5**	**3.5**	**-3.5**
SP	Count	257	366	240	383	251	372
	Adj. Residual	**-5.8**	**5.8**	**-6.9**	**6.9**	**-4.8**	**4.8**
VVD	Count	58	407	259	206	139	326
	Adj. Residual	**-17.5**	**17.5**	1.5	-1.5	**-8.6**	**8.6**

The Chi²-test showed that the cross table had significant differences for 'reactions', $\chi^2(12, N = 26590) = 13037.066$, $p < .001$, 'retweets', $\chi^2(12, N = 26590) = 11927.715$, $p < .001$, and 'likes', $\chi^2(12, N = 26590) = 12337.928$, $p < .001$. According to the residuals, list pullers from GL, PVV, and SP triggered significantly more reactions, retweets, and likes regardless of the topic of the tweet. The residuals also show that list pullers from D66, DENK, and VVD only triggered significantly more reactions, and likes. Other parties triggered overall significantly less interaction based on the residuals regardless of the topic of the tweet.

4.4.2 Timing

The following paragraphs present the results with regard to 'timing', including in which week of the election tweets were sent, the day of the week on which tweets were sent, and the hour of the day on which tweets were sent.

Week of the election

Figure 7 shows the distribution of the tweets sent by the list pullers over the weeks of the election. From the fourth week (January 9 until January 15) the amount of tweets per week kept increasing, leading up to a total of 202 tweets sent in week eight (February 6 until February 12). Only in the twelfth week (March 6 until March 12) the amount of tweets was higher than in week eight, with 220 tweets in that week. The relatively low amount of tweets during the fourteenth week (N = 55) can be (partially) explained by the fact that the last week of the elections lasted only from March 20 until March 23.

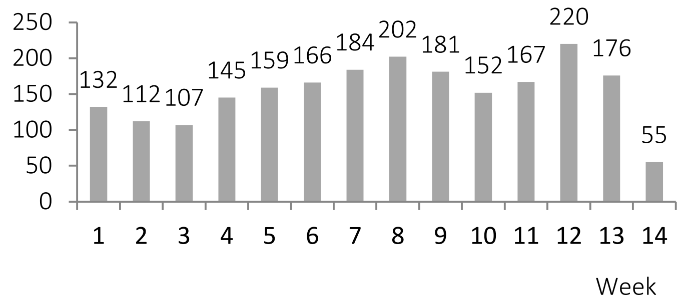

Figure 7: *Frequencies per week of the election*

With a Chi²-test (Appendix C, Table C3) it was possible to determine significant differences in amounts of interaction per week of the election ('reactions', $\chi^2(13, N = 2158) = 41.693$, $p < .001$, 'retweets', $\chi^2(13, N = 2158) = 35.848$, $p = .001$, 'likes', $\chi^2(13, N = 2158) = 83.103$, $p < .001$). In Table C1 of Appendix C it can be seen that tweets from week four triggered significantly less interaction, and that tweets from week twelve triggered significantly more interaction.

Day of the week

The results in Figure 8 indicate that the most popular days to send tweets were Mondays (N = 336), Saturdays (N = 325), and Thursdays (N = 319). During the other days of the week, list pullers were not as active.

Table 15 shows on which days of the week a tweet triggered significantly more and less interaction. The Chi²-test (Appendix C, Table C3) showed that tweets sent on Sunday ('reactions', $\chi^2(6, N = 2158) = 18.083$, $p = .006$, 'retweets', $\chi^2(6, N = 2158) = 19.923$, $p = .001$, 'likes', $\chi^2(6, N = 2158) = 15.860$, $p = .015$) resulted in significantly more interaction.

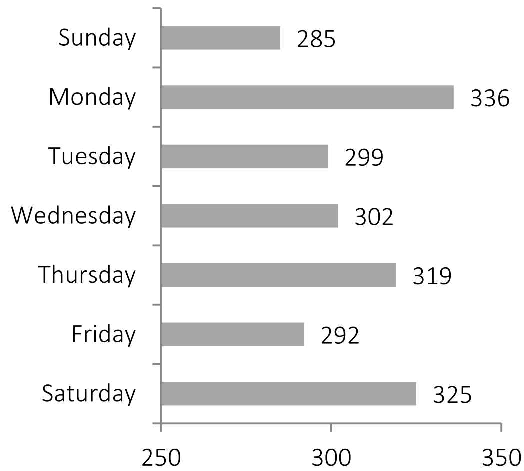

Figure 8: *Frequencies for day of the week*

Table 15: *Results for day of the week*

		Reactions		Retweets		Likes	
		Low	High	Low	High	Low	High
Sunday	Count	119	166	124	161	126	159
	Adj. Residual	**-3.6**	**3.6**	**-2.5**	**2.5**	**-2.3**	**2.3**
Monday	Count	189	147	180	156	181	155
	Adj. Residual	1.8	-1.8	1.3	-1.3	1.3	-1.3
Tuesday	Count	150	149	136	163	147	152
	Adj. Residual	-0.6	0.6	-1.8	1.8	-0.5	0.5
Wednesday	Count	158	149	162	140	152	150
	Adj. Residual	0.2	-0.2	-1.2	1.2	-0.1	0.1
Thursday	Count	162	157	159	160	167	152
	Adj. Residual	-0.3	0.3	-0.2	0.2	0.7	-0.7
Friday	Count	167	125	171	121	169	123
	Adj. Residual	**2.0**	**-2.0**	**3.0**	**-3.0**	**2.7**	**-2.7**
Saturday	Count	170	155	154	171	149	176
	Adj. Residual	0.3	-0.3	-1.2	1.2	-1.8	1.8

Hour of the day

Tweet activity from list pullers appears in general throughout the whole day. The most active moments are between 8:00h and 8:59h (*N* = 159), between 09:00h and 09:59h (*N* = 162), and between 12:00h and 12:59h (*N* = 155). Figure 9 also shows that the least tweets were sent between 22:00h (*N* = 72) and 7:59h (*N* = 91).

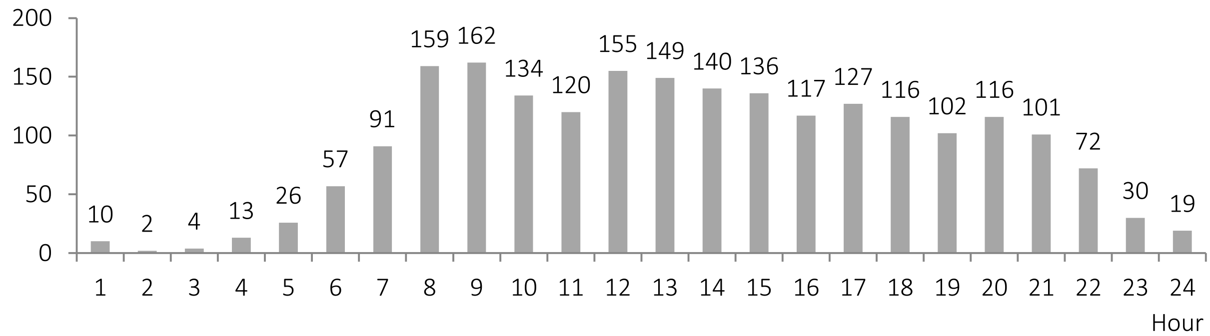

Figure 9: *Frequencies for hour of the day*

The only significant difference was found from 16:00h until 16:59h (Appendix C, Table C2). Tweets sent during the sixteenth hour of the day (‘reactions’, $\chi^2(23, N = 2158) = 35.455$, $p < .047$, ‘retweets’, $\chi^2(23, N = 2158) = 40.328$, $p = .014$, ‘likes’, $\chi^2(23, N = 2158) = 33.663$, $p = .070$) led to significantly more interaction than expected.

5. Discussion

As the theoretical framework has shown, a message on Twitter consists of a number of aspects. All of these aspects are more or less able to trigger interaction from other users of the social media platform Twitter, as was shown in the results section. This chapter delves into the implications of these results, and relates them back to theory. Furthermore, the discussion includes the limitations of the study, suggestions for future research on political interaction on social media, and a concise conclusion.

5.1 Interpretation of findings

The results showed that the interaction variables reactions, retweets, and likes all correlate with each other on a moderate or high level. This means that when there is a large amount of reactions on a tweet, it can be expected that there will also be a large amount of retweets and likes. The same goes for retweets and likes. This following section interprets the findings of this research further.

5.1.1 Topic and issue category

The topic and issue category is the category from which list pullers on Twitter can gain most profit if they desire an increase of interaction. First, the findings for the topic of the tweets showed that, in contrast to the expectations based on Bennett’s (2012) work, list pullers mostly addressed public instead of private topics. The more private topics did not trigger more interaction as well, thus the benefits of Marwick and Boyd's (2011) performative intimacy did not show in this research. Additionally, it was found that Twitter users mostly tend to respond to tweets that regard topics with an international aspect, as opposed to tweets about issues with a national character. Second, the results showed that not adding visual content to a tweet led to significantly less interaction, so adding a picture is advisable, which is in line with the expectation about the glimpse into the life of a politician based on Marwick and Boyd (2012). However, to trigger interaction, visual content does not have to be private as was expected based on Kaneko and Yanai’s (2013) work. Third, the work of Zappavigna (2011) on linguistic markers suggested that adding interactive features to a tweet would result in more interaction. The interactive features only trigger more interaction in the case of hashtags and in the case of emoticons. URL’s lead attention away from the tweets which might be the reason why tweets with URL’s results in less interaction. Also, bringing “other voices into tweets by addressing other users” as Zappavigna (2011, p.790) suggested leads to significantly less response, which can be explained by the fact that a tweet targeted at one or more specific Twitter accounts does not usually interest a broad public (Naveed, Gottron, Kunegis & Alhadi, 2011).

5.1.2 Opinion and sentiment category

The findings from the opinion and sentiment category follow the ones from the topic and issue category with regard to importance. The finding that slightly negative tweets trigger more interaction might be explained by Naveed, Gottron, Kunegis and Alhadi's (2011) statement that bad news disseminates fast on Twitter. This statement could also explain why humorous tweets are only more positively appealing, but do not trigger redistribution and reactions.

5.1.3 Structural category

The structural category appeared to be the least important when it concerns triggering interaction on Twitter, as mentioning actors generally led to less interaction. The expectation that mentioning influential actors leads to more interaction than mentioning less influential actors is only true mentioning international politicians. These findings can be explained by fact that tweets with a very specific target are not very interesting for a broad audience, whereas tweets that address broader public interests do trigger that interest (Naveed, Gottron, Kunegis & Alhadi, 2011).

5.1.4 Additional content

Additional content was measured by the codes network characteristics, candidate characteristics, and timing. It was expected that, without regarding the amount of followers or the topic of the tweet, electoral candidates with the same position on the list of their party would trigger the same amount of response. However, this appeared not to be true, as some list pullers triggered significantly more or less interaction than others. Considering timing, it appears that it does not really matter when a list puller sends a message with regard to the interaction that the message triggers. However, there are some significant results indicating preferable moments to send tweets that need to trigger interaction, which proves the expectation of timing to be true.

5.2 Implications for political communication

The findings from this study have implications for the development of the third phase of political communication. The third phase is characterized by the competitive environment in which politicians and political parties have to compete for the attention of potential voters (Blumler & Kavanagh, 1999), because there are many political voices present on the Internet (Dahlgren, 2005). Therefore, politicians have a great advantage if they are able to capture an audience's attention in this competitive environment. Having the ability to create interaction is a way to capture attention from potential voters. Politicians who start focussing on interaction can gain the advantage of attention in political communication. Furthermore, the findings of this research give way to the development of social media strategies that focus on triggering interaction from citizens instead of only communicating one way. Focusing social media strategies on creating interaction implies an online political sphere in which citizens can converse with politicians and other citizens, leading to a more transparent democracy in which citizens are more involved in political decision-making.

5.3 Limitations

This study has some limitations that are important to take into account. The first limitation of this research regards the codebook which was pre-tested and adapted in accordance with the discussion with the second coder. Because the adapted version of the codebook was not pre-tested again, it cannot be stated with complete certainty that the adapted codes are now sufficiently reliable. Second, this research mostly focused on the results of the original tweets altogether. Although the network and candidate characteristics were explored to some extent, future research might benefit from investigating individual politicians. Such a research offers insight in why some politicians on Twitter are more successful at triggering interaction than others. That knowledge can be used to create a Twitter strategy for politicians that aim for interaction. Third, this research focused on exploring which content from list pullers would lead to more interaction on Twitter. Therefore it is now known what type of content triggers interaction, but it cannot be explained why this content triggers interaction. Future research could focus on why, for example, certain topics or pictures, or a tone lead to more response as opposed to alternatives. Besides, further research can benefit from investigating what this interaction is about, and on the relation between election outcomes and use of interaction.

5.4 Conclusion

This research attempted to find out which content on Twitter from list pullers would trigger most interaction from other users. In order to investigate this, the content of a tweet was split into the three content categories for social media analytics in a political context by Stieglitz and Dang-Xuan (2013). Due to this research, it is now possible to conclude that if list pullers aim at triggering interaction with their tweets, they should focus especially on the topic and issue category. By picking topics, visual content, and interactive features properly, politicians should be able to start conversations between Twitter users, ensure that their messages will be redistributed more often, and appear convincing and appealing to other users which generates more likes. Focusing more on creating interaction would imply a shift in the way contemporary political communication takes place. This will show mostly in the social media strategies of politicians and the involvement of citizens in political communication. Political communication will change from one-way broadcasting to a dynamic and complex conversation in which more people will be actively involved than ever before.

Literature

Allen, R. (2017, February 23). *Top social network sites by number of active users 2017*. Retrieved on July 1, 2017, from Smart Insights.

Barberá, P., Jost, J. T., Nagler, J., Tucker, J. A., & Bonneau, R. (2015). Tweeting from left to right: Is online political communication more than an echo chamber? *Psychological Science, 26*(10), 1531-1542.

Baum, M. A., & Groeling, T. (2008). New media and the polarization of American political discourse. *Political Communication, 25*(4), 345-365.

Bennett, W. L. (2012). The personalization of politics political identity, social media, and changing patterns of participation. *The ANNALS of the American Academy of Political and Social Sciences, 644*(1), 20-39.

Bennett, W. L., & Iyengar, S. (2008). A new era of minimal effects? The changing foundations of political communication. *Journal of Communication, 58*(4), 707-731.

Blumler, J., & Kavanagh, D. (1999). The third age of political communication: Influences and features. *Political Communication, 16*(3), 209-230.

Chalofsky, N., & Cavallero, L. (2013). A good living versus a good life: Meaning, purpose, and HRD. *Advances in Developing Human Resources, 15*(4), 331-340.

Dahlgren, P. (2005). The internet, public spheres, and political communication: Dispersion and deliberation. *Political Communication, 22*(2), 147-162.

Diakopoulos, N. A., & Shamma, D. A. (2010, April). Characterizing debate performance via aggregated twitter sentiment. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems,* 1195-1198. ACM.

Downey, J., & Fenton, N. (2003). New media, counter publicity and the public sphere. *New Media & Society, 5*(2), 185-202.

Druckman, J. N. (2004). Priming the vote: Campaign effects in a U.S. Senate election. *Political Psychology, 25(*4), 577-594.

Fernandes, J., Giurcanu, M., Bowers, K. W., & Neely, J. C. (2010). The writing on the wall: A content analysis of college students' Facebook groups for the 2008 presidential election. *Mass Communication and Society, 13*(5), 653-675.

Foot, K. A., Schneider, S. M., & Dougherty, M. (2007). Online structure for political action in the 2004 US congressional electoral web sphere. In Kluver, R., Jankowski, N., Foot, K., & Schneider, S. M. (Red.), *The internet and national elections: A comparative study of web campaigning* (92-104). London: Routledge.

Graham, T., Broersma, M., Hazelhoff, K., & Van ’t Haar, G. (2013). Between broadcasting political messages and interacting with voters: The use of Twitter during the 2010 UK general election campaign. *Information, Communication & Society, 16*(5), 692-716.

Graham, T., Jackson, D., & Boersma, M. (2016). New platform, old habits? Candidates’ use of Twitter during the 2010 British and Dutch general election campaigns. *New Media & Society, 18*(5), 765-783.

Gurevitch, M., Coleman, S., & Blumler, J. G. (2009). Political communication: Old and new media relationships. *The ANNALS of the American Academy of Political and Social Science, 625*(1), 164-181.

Halberstam, Y., & Knight, B. (2016). Homophily, group size, and the diffusion of political information in social networks: Evidence from Twitter. *Journal of Public Economics, 143*(1), 73-88.

Johnson, T. J., & Kaye, B. K. (2000). Using is believing: The influence of reliance on the credibility of online political information among politically interested Internet users. *Journalism & Mass Communication Quarterly, 77*(4), 865-879.

Kamerbreed (n.d.). Overzicht partijprogramma’s. Retrieved on June 12, 2017, from http://www.ka-merbreed.info/home/?page_id=607.

Kaneko, T., & Yanai, K. (2013, July). Visual event mining from geo-tweet photos. In *Multimedia and Expo Workshops (ICMEW), 2013 IEEE International Conference on,* 1-6. IEEE.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons, 53*(1), 59-68.

Kieskompas (2017). *Politiek landschap.* Retrieved on September 6, 2017, from Kieskompas.

Kieswet (2001, December 20). *Hoofdstuk C: De zittingsduur van de leden van de Tweede Kamer der Staten-Generaal, van provinciale staten, van de algemene besturen en van de gemeenteraden.* Retrieved on April 28, 2017, from http://wetten.overheid.nl/BWBR0004627/2016-01-01.

Klinger, U., & Svensson, J. (2014). The emergence of network media logic in political communication: A theoretical approach. *New Media & Society, 17*(8), 1241-1257.

Knobloch-Westerwick, S., & Meng, J. (2009). Looking the other way: Selective exposure to attitude-consistent and counterattitudinal political information. *Communication Research, 36*(2), 426-448.

Lammers, J., Pelzer, B., Hendrickx, J., & Eisinga, R. (2007). *Categorische data analyse met SPSS: Inleiding in loglineaire analysetechnieken.* Assen: Koninklijke Van Gorcum BV.

Laroche, M., Habibi, M. R., Richard, M. O., Sankaranarayanan, R. (2012). The effects of social media based brand communities on brand community markers, value creation practices, brand trust and brand loyalty. *Computers in Human Behaviour, 28*(5), 1755-1767.

Mangold, W. G., & Faulds, D. J. (2009). Social media: The new hybrid element of the promotion mix. *Business Horizons, 52*(4), 357-365.

Markwick, A., & Boyd, D. (2011). To see and to be seen: Celebrity practice on Twitter. *Convergence, 17*(2), 139-158.

Meyer, J. C. (2000). Humor as a double-edged sword: Four functions of humor in communication. *Communication Theory, 10*(3), 310-331.

Moeller, J., De Vreese, C., Esser, F., & Kunz, R. (2014). Pathway to political participation: The influence of online and offline news media on internal efficacy and turnout of first-time voters. *American Behavioral Scientist, 58*(5), 689-700.

Naveed, N., Gottron, T., Kunegis, J., & Alhadi, A. C. (2011, June). Bad news travel fast: A content-based analysis of interestingness on Twitter. In *Proceedings of the 3rd International Web Science Conference.* ACM.

Raz, Y. (2012, June). Automatic humor classification on Twitter. In *Proceeding of the 2012 Conference on the North American Chapter of the Association for Computational Linguistics: Human Language Technologies: Student Research Workshop,* 66-70. Association for Computational Linguistics.

Semetko, H. A., & Valkenburg, P. M. (2000). Framing European politics: A content analysis of press and television news. *Journal of Communication, 50*(2), 93-109.

Shirky, C. (2011). The political power of social media: Technology, the public sphere, and political change. *Foreign Affairs,* 28-41.

Spierings, N., & Jacobs, K. (2014). Getting personal? The impact of social media on preferential voting. *Political Behavior, 36*(1), 215-234.

Stemler, S. (2001). An overview of content analysis. *Practical assessment, research & evaluation, 7*(17), 137-146.

Stieglitz, S., & Dang-Xuan, L. (2013). Social media and political communication: A social media analytics framework. *Social Network Analysis and Mining, 3*(4), 1277-1291.

Sweetser Trammell, K. D. (2007). Candidate campaign blogs: Directly reaching out to the youth vote. *American Behavioral Scientist, 50*(9), 1255-1263.

Tweede Kamer der Staten-Generaal (n.d.). *Verkiezingen 2017.* Retrieved on March 1, 2017, from https://www.tweedekamer.nl/vergaderingen/uitgelicht/verkiezingen-2017.

Vaccari, C. (2008). From the air to the ground: The internet in the 2004 US presidential campaign. *New Media & Society, 10*(4), 647-665.

Van der Veer, N., Boekee, S., & Peters, O. (2017, January 23). *Nationale social media onderzoek 2017: Het grootste trendonderzoek van Nederland naar het gebruik en verwachtingen van social media #NSMO*. Retrieved on July 2, 2017, from Newcom Research & Consultancy B.V.

Vergeer, M., & Hermans, L. (2013). Campaigning on Twitter: Microblogging and online social networking as campaign tools in the 2010 general elections in the Netherlands. *Journal of Computer-Mediated Communication, 18*(4), 399-419.

Vergeer, M., Hermans, L., & Sams, S. (2011). Online social networks and micro-blogging in political campaigning: The exploration of a new campaign tool and a new campaign style. *Party Politics, 19*(3), 477-501.

Vollman, A. (2011, February 10). The Netherlands lead global markets in Twitter.com reach. Retrieved on May 10, 2017, from ComScore.

De Vreese, C. H., Banducci, S. A., Semetko, H. A., & Boomgaarden, H. G. (2005). The news coverage of the 2004 European parliamentary election campaign in 25 countries. *European Union Politics, 7*(4), 477-504.

De Vries, L., Gensler, S., & Leeflang, P. S. (2012). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. *Journal of Interactive Marketing, 26*(2), 83-91.

White, M. D., & Marsh, E. E. (2006). Content analysis: A flexible methodology. *Library trends, 55*(1), 22-45.

Zappavigna, M. (2011). Ambient affiliation: A linguistic perspective on Twitter. *New Media & Society, 13*(5), 788-806.

Zhang, R., & Liu, N. (2014, November). Recognizing humor on Twitter. In *Proceedings of the 23rd ACM International Conference on Information and Knowledge Management.* ACM.

Appendices

Appendix A – Codebook

The following pages contain the codebook used in this research.

Code	Code number	Explanation	Code	Example
Tweet ID	1	ID of the tweet	18 number ID	“810853649480085504”
Network characteristics	2	Amount of followers	Number of Twitter users following the candidate	“15488”
	3	Amount of people followed by the candidate	Number of Twitters users that the candidate follows	“218”
Candidate characteristics	4	Party the candidate is associated with	1 = 50PLUS	“@HenkKrol”
			2 = CDA	“@sybrandbuma”
			3 = ChristenUnie	“@gertjansegers”
			4 = D66	“@APechtold”
			5 = GroenLinks	“@jesseklaver”
			6 = PvdA	“@LodewijkA”
			7 = PvdD	“@mariannethieme”
			8 = PVV	“@geertwilderspvv”
			9 = SGP	“@keesvdstaaij”
			10 = SP	“@emileroemer”
			11 = VVD	“@minpres”
			12 = Forum voor Democratie	“@thierrybaudet”
			13 = DENK	“@tunahankuzu”
Timing tweet	5	Day of the week that the original tweet was sent by the candidate	1 = Sunday	“Sun”
			2 = Monday	“Mon”
			3 = Tuesday	“Tue”
			4 = Wednesday	“Wed”
			5 = Thursday	“Thu”
			6 = Friday	“Fri”
			7 = Saturday	“Sat”
	6	Date and time of the original tweet being sent	dd-mm-yyyy hh:mm	“23-12-2016 14:45”
Interaction - reactions	7	Number of reactions on the original tweet		“11”
Interaction - retweets	8	Number of retweets the original tweet received		“12”
Interaction - likes	9	Number of likes the original tweet received		“11”
Presence of hashtags (‘#’) in the tweet	10	Application of hashtags (reference to a certain topic) in the original tweet.	0 = No	No hashtag in the original tweet
			1 = Yes	“15 maart 2017 #NederlandWeerVanOns https://t.co/tNuJ5M7sgH”
Presence of @-mentions (‘@’) in the tweet	11	Application of a @-mention (involving a user in a tweet or conversation) in the original tweet	0 = No	No @-mention in the original tweet
			1 = Yes	“Ach beste Attje, lees ons verkiezingsprogramma en u piept heel anders. Uw ex-stemmers weten wel beter. @attjekuiken in de PvdA-Nieuwsbrief:”
Presence of a poll in the	12	Application of a poll (asking users a multiple	0 = No	No poll in the original tweet

tweet		choice question) in the original tweet	1 = Yes	“Kerken krijgen gegevens van de burgerlijke stand. Is dat gepast?”
Actors (involved in original tweet)	13	The original tweet involves a citizen using a @-mention	0 = No	No citizens mentioned
			1 = Yes	“Goed gesprek over prostitutie en mensenhandel gehad. Met een betrokken zaal en olv @MeijerHerman https://twitter.com/gidsmatthijs/status/819270479823405057 …”
	14	The original tweet involves another politician from the sender’s party using a @-mention	0 = No	No politician from sender’s party
			1 = Yes	“Nu dus tijd voor #ADR @piadijkstra https://t.co/4M4eZaQC5e”
	15	The original tweet involves a politician from another Dutch political party using a @-mention	0 =No	No politician from another party
			1 = Yes	“Dank, @keesvdstaaij Steun ook de hulp aan tienermoeders! Een initiatief van @vbokNL en @christenunie Zie: tienermoederfonds.nl”
	16	The original tweet involves the sender’s own party using a @-mention	0 = No	No mention of sender’s own party
			1 = Yes	“Volgtip: @GladysDENK en @StephanvBaarle. Respectievelijk #4 en #5 van de kandidatenlijst van @DenkNL”
	17	The original tweet involves another Dutch party using a @-mention	0 = No	No mention of another party
			1 = Yes	“Even over @DenkNL: als je de grenzen openzet en 100.000en van dit soort lui binnenhaalt moet je niet verbaasd zijn als ze zich organiseren.” (From Thierry Baudet)
	18	The original tweet involves a Dutch politician outside of the House of Representatives (e.g. mayors or aldermen) using a @-mention	0 = No	No mention of other Dutch politician
			1 = Yes	“Volgens Blok (VVD) bouwt @LaurensIvens teveel sociale huur. Mooier compliment kun je als SP-wethouder niet krijgen. https://t.co/9uJ5OleUAH”
	19	The original tweet involves an international politician using a @-mention	0 = No	No mention of international politician
			1 = Yes	Vandaag de Poolse MP @BeataSzydlo ontvangen in het Catshuis. → https://www.facebook.com/ministerpresid
	20	The original tweet involves an international party using a @-mention	0 = No	No mention of international party
			1 = Yes	“Very good @EmmanuelMacron! Let's work together - also with @timfarron @LibDems! - on a powerful progressive movement in Europe!”
	21	The original tweet involves media (channels and/or journalists, presenters, etc. for media channels) using a @-mention	0 = No	No mention of media
			1 = Yes	“Vanaf 09:30 uur zit ik met @arnoldkarskens Herna Verhagen en Margriet Sitskoorn op de bank bij @rickniemann @WNLOpZondag @NPO1”
	22	The original tweet involves a government organization using a @-mention	0 = No	No mention of government organization
			1 = Yes	“oud inspectr-generaal @_NVWA:"t ontbreekt de vleesindustrie nog steeds aan voldoende ethisch besef" #vleesschandaal”
	23	The original tweet involves a non-profit organization using a @-mention	0 = No	No mention of non-profit organization
			1 = Yes	“200 mensen gaan zo in Voorthuizen het koude water in. Voor projecten van @worldservants Ik mag het startschot geven: https://t.co/s6vwA2vTOC”
	24	The original tweet involves a commercial organization using a @-mention	0 = No	No mention of commercial organization
			1 = Yes	“Ontvangen door vader & zoon van der Leegte bij @VDL_Groep in

				Eindhoven en Born. Onder de indruk van onze automotive industrie. #banenmotor”
	25	The original tweet involves an Interest group using a @-mention	0 = No	No mention of an interest group
			1 = Yes	“Dank, @keesvdstaaij Steun ook de hulp aan tienermoeders! Een initiatief van @vbokNL en @christenunie Zie: http://www.tienermoederfonds.nl“
	26	The original tweet involves another actor using a @-mention	0 = No	No mention of other actors
			1 = Yes	“De mooi verlichte Oude Kerk in Voorburg in afwachting van de @PKNnl Kerstnachtdienst. https://t.co/7Ql7tz5PaX”
Content	27	The topic that the original tweet is about (the most important or prominent topic of the tweet)	1 = War/terrorism	“Afschuwelijke terreurdaad in Canada https://t.co/JIfCSUgqoq”
			2 = Economy/financial affairs/taxes	“Goede cijfers van CBS over economie. Het consumentenvertrouwen is hoog en in 2016 sterkste daling werkloosheid in t… https://t.co/gKnm3oc0NB”
			3 = Security/defence	“Vanmorgen in de krant: een kerstgroet voor ál onze militairen. Zij vechten voor vrede! https://t.co/sGyWPlInIE”
			4 = Commenting on government (e.g. current policy, other politicians)	“NL heeft goede politieke en economische relaties met beide landen. Ook in kader van NLse zetel in VNVR zullen we nauw samenwerken. (3/3)”
			5 = International issues/foreign policy	“Vanochtend gebeld met de nieuwe premier van Nieuw-Zeeland en hem gefeliciteerd met benoeming. Oa teruggeblikt op geslaagd staatsbezoek.(1/3)”
			6 = Education	“Collega Klaver vroeg me 'naar links' te kijken en toen zag ik wat daar met onderwijsvrijheid gebeurde.. #Trouw https://t.co/rWjBK9S4c9”
			7 = Health care	“In de zorg moet het gaan om empathie, niet een mentaliteit van ieder-voor-zich. Onze plannen� #stemvoorverandering https://t.co/WEPYiAxfO6”
			8 = Europe	“‘Which Europe now?’ Watch the @wef session I'm in at https://t.co/BVgwRkYOoF #wef17”
			9 = Social affairs and employment	“Welke veranderingen zijn vandaag ingegaan op sociale zaken? https://t.co/va7T6Qh9Es”
			10 = Media and culture	“Mooie lokale traditie rond oud en nieuw. Met @cdavandaag in Voorburg oliebollen rondgebracht bij de ouderen in de g… https://t.co/ZnBo5ArBLn”
			11 = Integration/Refugee policy	“Dus Anis Amri komt EU binnen als azielzoeker, pleegt terreurdaad in Dld en reist daarna naar Italië. En grenzen dicht mag niet @MinPres?”
			12 = Citizen and governance	“Strijdmakker Vliegenthart knokt elke dag om Amsterdammers die niet worden gehoord een stem te geven. Mooi stuk: https://t.co/YgHIrg1NZH”
			13 = Environment	“Het kabinet houdt kolencentrales open. GroenLinks kiest voor het meest ambitieuze klimaatbeleid ooit. #stemvoorverandering”
			14 = Animals	“Arctic fox in Churchill, Canada by Norbert Rosing via @Fascinatingpics https://t.co/Px0j621ew3”

			15 = Public transportation / infrastructure	“Volgens Blok (VVD) bouwt @LaurensIvens teveel sociale huur. Mooier compliment kun je als SP-wethouder niet krijgen. https://t.co/9uJ5OleUAH”
			16 = Campaign activities	“Druk met de voorbereiding van de teambuildingsweek voor de 12 eerste kandidaten van 50PLUS voor de verkiezingen. Op 2/1 gaan we de hei op.”
			17 = Family/friends	“Dapper! Onze medewerkster Cherine wil weten waar ze vandaan komt en ging met @SpoorloosTV op zoek naar haar familie… https://t.co/CtwM0t2tT0”
			18 = Religion	“Zoveel mensen die uitzagen naar Kerst en nu zoveel verdriet. Heer, ontferm U over ons.. #Berlijn”
			19 = Home	“Veel dank voor de vele tips over omgang met de ipad die ik de laatste dagen mocht ontvangen.”
			20 = Leisure/sports/ hobbies	“Prachtige overwinning voor Michael van Gerwen bij het WK Darten. Ik heb @MvG180 zojuist gefeliciteerd met zijn tweede wereldtitel!”
			21 = Celebration	“In Caïro heb ik Kerst leren vieren: https://t.co/ZBOthOaIrJ https://t.co/35d6m1pFpt”
			22 = Multiple topics	“Merkel, Rutte en alle andere laffe regeringsleiders hebben met hun opengrenzenpolitiek de asieltsunami en islamterreur binnengelaten.”
			23 = Other	“Niet zo jaloers Alexander, er kan er maar één de beste zijn! https://t.co/qH4fFqm75M”
Visual content	28	Professional visual content to enhance the image of the politician and private visual content revealing something from a politician’s personal life	0 = Not applicable	Tweets without visual content
			1 = Formal publicity	“Nederland bedankt! https://t.co/f1T6YGulha“
			2 = Corporate visual identity (e.g. logos, campaign material)	“Bijna uitverkocht! Al 1000 mensen komen naar ons verkiezingscongres. Zie ik je daar? Meld je snel aan! > http://d66.nl/congres “
			3 = Food	“De Japanse stad Shanghai? @Aldi https://t.co/1qUKhqrnKv”
			4 = Weather	“De zon komt op boven de Moerdijk. Op weg naar Venlo oa voor de @cdavandaag nieuwjaarsbijeenkomst. https://t.co/WmEbOf5EwD”
			5 = Street scenes	“De mooi verlichte Oude Kerk in Voorburg in afwachting van de @PKNnl Kerstnachtdienst. https://t.co/7Ql7tz5PaX”
			6 = Events/activities	“In Caïro heb ik Kerst leren vieren: christenunie.nl/kerstincairo https://t.co/ZBOthOalrJ”
			7 = Text/media (pieces with text and/or media articles)	“Kloppen de lage werkloosheidscijfers? https://t.co/nsJUyvfov6”
			8 = Other	“Kerstmis 2016. Eindhoven. Boom in bloei; https://t.co/XfIQ4UV2lQ”
Emoticons	29	The use of visual expression through icons in the original tweet	0 = No	No use of emoticons
			1 = Yes	“100 mensen op het stadhuis aan de #Coolsingel in #Rotterdam die staan te popelen om een ondersteuningsverklaring te tekenen. 😄”

URL’s	30	If a tweet contains a link to another website	0 = No	No use of external links
			1 = Yes	“Dank, @keesvdstaaij Steun ook de hulp aan tienermoeders! Een initiatief van @vbokNL en @christenunie Zie: http://www.tienermoederfonds.nl”
Tone	31	Emotional valence ascribed to the message	1 = Negative (e.g. sad, angry, confused)	“Merkel, Rutte en alle andere laffe regeringsleiders hebben met hun opengrenzenpolitiek de asieltsunami en islamterreur binnengelaten.”
			2 = Non-evaluative (neutral)	“De vraag is: gaan we naar links of naar rechts. De kiezer heeft recht op dit debat. (2/3)”
			3 = Positive (e.g. happy, satisfied, excited, curious)	“Nederland bedankt! https://t.co/f1T6YGulha“
			4 = Mixed (tweet tackles positive as well as negative side)	“Nederland heeft een premier nodig die vasthoudt aan zijn idealen. Daarom wil ik jullie premier worden... https://t.co/kgDuskx96x”
Humour	32	Making use of humour in a tweet (e.g. jokes, wordplay, sarcasm, irony)	0 = No	No use of humour
			1 = Yes	“Tot vrijdag zou ik gezegd hebben: het Haagse Plein is leeg. Nu zeg ik: nog nooit was de menigte voor mijn raam zo groot. #hartverwarmend”

Appendix B – Pre-test results for the actors

Table B1: *Pre-test results actors*

Code actors	Kappa	p-value	Confidence interval
Citizen	1.000	p < .005	95%
Politician sender's party	0.534	p < .005	95%
Politician other party	1.000	p < .005	95%
Own party	1.000	p < .005	95%
Other party[1]	-	-	-
Other politician[1]	-	-	-
International politician[1]	-	-	-
International party[1]	-	-	-
Media	0.961	p < .005	95%
Government organization[1]	-	-	-
Non-profit organization	0.660	p < .005	95%
Commercial organization	0.798	p < .005	95%
Citizen initiative[1]	-	-	-
Interest group	-0.006	p = .924	95%
Other	0.349	p < .005	95%

[1] Not present in pre-test sample

Appendix C – Analysis for timing

Table C1: *Cross table for week of the election*

		Reactions		Retweets		Likes	
		Low	High	Low	High	Low	High
1	Count	59	73	60	72	61	71
(19 Dec – 25 Dec)	Expected count	68.2	63.8	66.4	65.6	66.7	65.3
	Percentage	44.7%	55.3%	45.5%	54.5%	46.2%	53.8%
	Adj. residual	-1.7	1.7	-1.2	1.2	-1.0	1.0
2	Count	55	57	60	52	56	56
(26 Dec – 1 Jan)	Expected count	57.9	54.1	56.4	55.6	56.6	55.4
	Percentage	49.1%	50.9%	53.6%	46.4%	50.0%	50.0%
	Adj. residual	-0.6	0.6	0.7	-0.7	-0.1	0.1
3	Count	64	43	60	47	67	40
(2 Jan – 8 Jan)	Expected count	55.3	51.7	53.8	53.2	54.1	52.9
	Percentage	59.8%	40.2%	56.1%	43.9%	62.6%	37.4%
	Adj. residual	1.7	-1.7	1.2	-1.2	**2.6**	**-2.6**
4	Count	98	47	99	46	107	38
(9 jan – 15 jan)	Expected count	74.9	70.1	73.0	72.0	73.3	71.7
	Percentage	67.6%	32.4%	68.3%	31.7%	73.8%	26.2%
	Adj. residual	**4.0**	**-4.0**	**4.5**	**-4.5**	**5.8**	**-5.8**
5	Count	92	67	89	70	97	62
(16 Jan – 22 Jan)	Expected count	82.2	76.8	80.0	79.0	80.4	78.6
	Percentage	57.9%	42.1%	56.0%	44.0%	61.0%	39.0%
	Adj. residual	1.6	-1.6	1.5	-1.5	**2.7**	**-2.7**
6	Count	83	83	80	86	91	75
(23 Jan – 29 Jan)	Expected count	85.8	80.2	83.5	82.5	83.9	82.1
	Percentage	50.0%	50.0%	48.2%	51.8%	54.8%	45.2%
	Adj. residual	-0.4	0.4	-0.6	0.6	1.1	-1.1
7	Count	105	79	96	88	101	83

(30 Jan – 5 Feb)	Expected count	95.1	88.9	92.6	91.4	93.0	91.0
	Percentage	57.1%	42.9%	52.2%	47.8%	54.9%	45.1%
	Adj. residual	1.5	-1.5	0.5	-0.5	1.2	-1.2
8	Count	101	101	102	100	96	106
(6 Feb – 12 Feb)	Expected count	104.4	97.6	101.7	100.3	102.1	99.9
	Percentage	50.0%	50.0%	50.5%	49.5%	47.5%	52.5%
	Adj. residual	-0.5	0.5	0.1	-0.1	-0.9	0.9
9	Count	96	85	94	87	100	81
(13 Feb – 19 Feb)	Expected count	93.5	87.5	91.1	89.9	91.5	89.5
	Percentage	53.0%	47.0%	51.9%	48.1%	55.2%	44.8%
	Adj. residual	0.4	-0.4	0.5	-0.5	1.3	-1.3
10	Count	64	88	66	86	69	83
(20 Feb – 26 Feb)	Expected count	78.5	73.5	76.5	75.5	76.8	75.2
	Percentage	42.1%	57.9%	43.4%	56.6%	45.4%	54.6%
	Adj. residual	**-2.4**	**2.4**	-1.8	1.8	-1.3	1.3
11	Count	91	76	76	91	72	95
(27 Feb – 5 Mar)	Expected count	86.3	80.7	84.0	83.0	84.4	82.6
	Percentage	54.5%	45.5%	45.5%	54.5%	43.1%	56.9%
	Adj. residual	0.8	-0.8	-1.3	1.3	**-2.0**	**2.0**
12	Count	94	126	96	124	87	133
(6 Mar – 12 Mar)	Expected count	113.7	106.3	110.7	109.3	111.2	108.8
	Percentage	42.7%	57.3%	43.6%	56.4%	39.5%	60.5%
	Adj. residual	**-2.8**	**2.8**	**-2.1**	**2.1**	**-3.4**	**3.4**
13	Count	91	85	86	90	70	106
(13 Mar – 19 Mar)	Expected count	90.9	85.1	88.6	87.4	89.0	87.0
	Percentage	51.7%	48.3%	48.9%	51.1%	39.8%	60.2%
	Adj. residual	0.0	0.0	-0.4	0.4	**-3.0**	**3.0**
14	Count	22	33	22	33	17	38
(20 Mar – 23 Mar)	Expected count	28.4	26.6	27.2	27.3	27.8	27.2
	Percentage	40.0%	60.0%	40.0%	60.0%	30.9%	69.1%
	Adj. residual	-1.8	1.8	-1.6	1.6	**-3.0**	**3.0**

Table C2: *Cross table for hour of the day*

		Reactions		Retweets		Likes	
		Low	High	Low	High	Low	High
1:00 – 1:59	Count	5	5	3	7	2	8
	Expected count	5.2	4.8	5.0	5.0	5.1	4.9
	Percentage	50.0%	50.0%	30.0%	70.0%	20.0%	80.0%
	Adj. residual	-0.1	0.1	-1.3	1.3	-1.9	1.9
2:00 – 2:59	Count	0	2	0	2	0	2
	Expected count	1.0	1.0	1.0	1.0	1.0	1.0
	Percentage	0.0%	100.0%	0.0%	100.0%	0.0%	100.0%
	Adj. residual	-1.5	1.5	-1.4	1.4	-1.4	1.4
3:00 – 3:59	Count	3	1	2	2	3	1
	Expected count	2.1	1.9	2.0	2.0	2.0	2.0
	Percentage	75.0%	25.0%	50.0%	50.0%	75.0%	25.0%
	Adj. residual	0.9	-0.9	0.0	0.0	1.0	-1.0
4:00 – 4:59	Count	8	5	8	5	8	5
	Expected count	6.7	6.3	6.5	6.5	6.6	6.4
	Percentage	61.5%	38.5%	61.5%	38.5%	61.5%	38.5%
	Adj. residual	0.7	-0.7	0.8	-0.8	0.8	-0.8
5:00 – 5:59	Count	17	9	19	7	18	8
	Expected count	13.4	12.6	13.1	12.9	13.1	12.9
	Percentage	65.4%	34.6%	73.1%	26.9%	69.2%	30.8%
	Adj. residual	1.4	-1.4	**2.3**	**-2.3**	1.9	-1.9
6:00 – 6:69	Count	25	32	24	33	29	28
	Expected count	29.5	27.5	28.7	28.3	28.8	28.2
	Percentage	43.9%	56.1%	42.1%	57.9%	50.9%	49.1%
	Adj. residual	-1.2	1.2	-1.3	1.3	0.0	0.0
7:00 – 7:59	Count	38	53	36	55	43	48
	Expected count	47.0	44.0	45.8	45.2	46.0	45.0
	Percentage	41.8%	58.2%	39.6%	60.4%	47.3%	52.7%
	Adj. residual	-1.9	1.9	**-2.1**	**2.1**	-0.6	0.6

8:00 – 8:59	Count	77	82	77	82	84	75
	Expected count	82.2	76.8	80.0	79.0	80.4	78.6
	Percentage	48.4%	51.6%	48.4%	51.6%	52.8%	47.2%
	Adj. residual	-0.8	0.8	-0.5	0.5	0.6	-0.6
9:00 – 9:59	Count	95	67	88	74	85	77
	Expected count	83.7	78.3	81.5	80.5	81.9	80.1
	Percentage	58.6%	41.4%	54.3%	45.7%	52.5%	47.5%
	Adj. residual	1.8	-1.8	1.1	-1.1	0.5	-0.5
10:00 – 10:59	Count	79	55	74	60	79	55
	Expected count	69.2	64.8	67.4	66.6	67.7	66.3
	Percentage	59.0%	41.0%	55.2%	44.8%	59.0%	41.0%
	Adj. residual	1.7	-1.7	1.2	-1.2	**2.0**	**-2.0**
11:00 – 11:59	Count	62	58	67	53	67	53
	Expected count	62.0	58.0	60.4	59.6	60.7	59.3
	Percentage	52.7	48.3%	55.8%	44.2%	55.8%	44.2%
	Adj. residual	0.0	0.0	1.2	-1.2	1.2	-1.2
12:00 – 12:59	Count	81	74	79	76	78	77
	Expected count	80.1	74.9	78.0	77.0	78.4	76.6
	Percentage	52.3%	47.7%	51.0%	49.0%	50.3%	49.7%
	Adj. residual	0.2	-0.2	0.2	-0.2	-0.1	0.1
13:00 – 13:59	Count	72	77	75	74	72	77
	Expected count	77.0	72.0	75.0	74.0	75.3	73.7
	Percentage	48.3	51.7%	50.3%	49.7%	48.3%	51.7%
	Adj. residual	-0.8	0.8	0.0	0.0	-0.6	0.6
14:00 – 14:59	Count	73	67	72	68	69	71
	Expected count	72.3	67.7	70.5	69.5	70.8	69.2
	Percentage	52.1%	47.9%	51.4%	48.6%	49.3%	50.7%
	Adj. residual	0.1	-0.1	0.3	-0.3	-0.3	0.3
15:00 – 15:59	Count	70	66	74	62	71	65
	Expected count	70.3	65.7	68.4	67.6	68.8	67.2
	Percentage	51.5%	48.5%	54.4%	45.6%	52.2%	47.8%
	Adj. residual	0.0	0.0	1.0	-1.0	0.4	-0.4
16:00 – 16:59	Count	49	68	41	76	47	70

	Expected count	60.5	56.5	58.9	58.1	59.2	57.8
	Percentage	41.9%	58.1%	35.0%	65.0%	40.2%	59.8%
	Adj. residual	**-2.2**	**2.2**	**-3.4**	**3.4**	**-2.3**	**2.3**
17:00 – 17:59	Count	59	68	58	69	57	70
	Expected count	65.6	61.4	63.9	63.1	64.2	62.8
	Percentage	46.5%	53.5%	45.7%	54.3%	44.9%	55.1%
	Adj. residual	-1.2	1.2	-1.1	1.1	-1.3	1.3
18:00 – 18:59	Count	58	58	60	56	54	62
	Expected count	59.9	56.1	58.4	57.6	58.6	57.4
	Percentage	50.0%	50.0%	51.7%	48.3%	46.6%	53.4%
	Adj. residual	-0.4	0.4	0.3	-0.3	-0.9	0.9
19:00 – 19:59	Count	57	45	48	54	51	51
	Expected count	52.7	49.3	51.3	50.7	51.6%	50.4
	Percentage	55.9%	44.1%	47.1%	52.9%	50.0%	50.0%
	Adj. residual	0.9	-0.9	-0.7	0.7	-0.1	0.1
20:00 – 20:59	Count	59	57	57	59	59	57
	Expected count	59.9	56.1	58.4	57.6	58.6	57.4
	Percentage	50.9%	49.1%	49.1%	50.9%	50.9%	49.1%
	Adj. residual	-0.2	0.2	-0.3	0.3	0.1	-0.1
21:00 – 21:59	Count	60	41	60	41	54	47
	Expected count	52.2	48.8	50.8	50.2	51.1	49.9
	Percentage	59.4%	40.6%	59.4%	40.6%	53.5%	46.5%
	Adj. residual	1.6	-1.6	1.9	-1.9	0.6	-0.6
22:00 – 22:59	Count	47	25	43	29	44	28
	Expected count	37.2	34.8	36.2	35.8	36.4	35.6
	Percentage	65.3%	34.7%	59.7%	40.3%	61.1%	38.9%
	Adj. residual	**2.4**	**-2.4**	1.6	-1.6	1.8	-1.8
23:00 – 23:59	Count	15	15	12	18	11	19
	Expected count	15.5	14.5	15.1	14.9	15.2	14.8
	Percentage	50.0%	50.0%	40.0%	60.0%	36.7%	63.3%
	Adj. residual	-0.2	0.2	-1.1	1.1	-1.5	1.5
24:00 – 00:59	Count	6	13	9	10	6	13
	Expected count	9.8	9.2	9.6	9.4	9.6	9.4

Percentage	31.6%	68.4%	47.4%	52.6%	31.6%	68.4%
Adj. residual	-1.8	1.8	-0.3	0.3	-1.7	1.7

Table C3: *Chi²-tests for timing*

Variable		Reactions	Retweets	Likes
Week of the election	Value	41.693	35.484	83.103
	Df	13	13	13
	Sig.	.000	.001	.000
Day of the week	Value	18.083	19.923	15.860
	Df	6	6	6
	Sig.	.006	.003	.015
Time per hour	Value	35.455	40.328	33.663
	Df	23	23	23
	Sig.	.047	.014	.070