Computer-assisted content analysis of Twitter data

Jessica Einspänner-Pflock
University of Bonn

Caja Thimm
University of Bonn

TWITTER AND SOCIETY

Digital Formations

Steve Jones
General Editor

Vol. 89

The Digital Formations series is part of the Peter Lang Media and Communication list.
Every volume is peer reviewed and meets
the highest quality standards for content and production.

PETER LANG
New York • Washington, D.C./Baltimore • Bern
Frankfurt • Berlin • Brussels • Vienna • Oxford

TWITTER AND SOCIETY

Edited by Katrin Weller, Axel Bruns,
Jean Burgess, Merja Mahrt, & Cornelius Puschmann

PETER LANG
New York • Washington, D.C./Baltimore • Bern
Frankfurt • Berlin • Brussels • Vienna • Oxford

Library of Congress Cataloging-in-Publication Data

Twitter and society / edited by Katrin Weller, Axel Bruns,
Jean Burgess, Merja Mahrt, Cornelius Puschmann.
pages cm. — (Digital formations; vol. 89)
Includes bibliographical references and index.
1. Twitter. 2. Online social networks. 3. Internet—Social aspects.
4. Information society. I. Weller, Katrin, editor of compilation.
HM743.T95T85 2 006.7'54—dc23 2013018788
ISBN 978-1-4331-2170-8 (hardcover)
ISBN 978-1-4331-2169-2 (paperback)
ISBN 978-1-4539-1170-9 (e-book)
ISSN 1526-3169

Bibliographic information published by **Die Deutsche Nationalbibliothek**.
Die Deutsche Nationalbibliothek lists this publication in the "Deutsche
Nationalbibliografie"; detailed bibliographic data is available
on the Internet at http://dnb.d-nb.de/.

Cover art:
Klee, Paul (1879–1940): *Twittering Machine* (*Zwitscher-Maschine*), 1922.
New York, Museum of Modern Art (MoMA).
Watercolor, and pen and ink on oil transfer drawing on paper, mounted on cardboard.

The paper in this book meets the guidelines for permanence and durability
of the Committee on Production Guidelines for Book Longevity
of the Council of Library Resources.

29 Broadway, 18th floor, New York, NY 10006
www.peterlang.com

Table of Contents

Part I: Concepts and Methods

CONCEPTS

METHODS

Part II: Perspectives and Practices

PERSPECTIVES

PRACTICES

POPULAR CULTURE

BRAND COMMUNICATION

POLITICS AND ACTIVISM

JOURNALISM

CRISIS COMMUNICATION

TWITTER IN ACADEMIA

Computer-Assisted Content Analysis of Twitter Data

8
CHAPTER

Jessica Einspänner, Mark Dang-Anh, and Caja Thimm

to understand what people are saying, special tools and methods are needed #CAQDAS

CONCEPTUAL OVERVIEW: STATE OF THE ART OF ONLINE CONTENT ANALYSIS

Content analysis can be understood as a methodological framework within which various approaches of textual and non-textual analyses can be applied. The research technique of content analysis facilitates the systematic coding and analysing of the content of spoken, written, or audio-visual communication (Berelson, 1952; Krippendorff, 2004). It is used in order to identify and classify words, phrases, or other meaningful matter, such as images, sounds, or even numerical records in terms of their structure and semantics. By interpreting frequency distributions and co-occurrence patterns of the single analytical units, this methodological approach allows for systematically drawing valid conclusions from data "to the context of their use" (Krippendorff, 2004, p. 18). Early content analyses trace back to the 17th century, when the Church started to examine the content of the first newspapers systematically (Krippendorff, 2004, p. 3). As a fully developed scientific method, however, content analysis was not employed until the 1940s, when it was used for analysing mass-media content (Herring, 2010). In the Information Age, the Internet has become an important means for interpersonal communication and social interaction. In order to assess the relevance of online communication, the "careful and systematic observation of its contents seems inevitable" (Rössler, 2002, p. 301). Chat protocols, weblog content, social network communication, or other multimedia content is especially of interest to researchers, as this kind of online communication is supposed to be "the bearer of human existence" (Capurro & Pingel, 2002, p. 192). Almost instant access to people's utterances, uploaded pictures, or videos that could give information about certain characteristics and preferences of their behaviour (e.g., consumption, political opinion, manners of interaction), make the online environment an attractive research area for politics, economy, and science. Following a broad interpretation such as proposed here, researchers often draw on content analysis as an established methodological framework, and extend its traditional concepts while applying them to the online world (Herring, 2010).

The objectives of a content analysis of Twitter data can be as diverse as the possible methodological procedures. For example, the metrics of tweets can be analysed, i.e. how many @replies did two particular users exchange within a certain hashtag-based discourse? Which were the most common phrases used by a certain group of users in the data set? It might also be interesting to go into a detailed qualitative analysis of the tweets and find out about, for example, the linguistic characteristics of Twitter language and its speech acts, argumentative schemas, or semantic co-occurrences. One might also want to compare the topics that emerge on Twitter and the types of users who talk about similar or diverging topics, for example, politicians versus citizens. The examination of conversational structures through Social Network Analysis (Magnani, Montesi, Nunziante, & Rossi, 2011)—which can be regarded as one form of content analysis (Herring, 2010)—is just as interesting as doing opinion mining through Sentiment Analysis (Kumar & Sebastian, 2012; Nielsen, 2011), or using a mixed-method approach—for instance, a combined statistical and hermeneutical analysis—in order to assess the diffusion of information on Twitter (Huang, Thornton, & Efthimiadis, 2010; Jansen, Zhang, Sobel, & Chowdury, 2009). Content analysis is an approach to empirical research based on pre-existing material. On Twitter, we deal with high amounts of naturally occurring data, i.e. data that is usually produced without being motivated by any research intent, unlike elicited data from interviews, surveys, etc. Traditionally, content analysis does not necessarily require special software, and might as well be carried out manually or with common spreadsheet software. However, due to the large sample sizes that can be collected for the analysis of Twitter data, we recommend using data analysis software to support the research process along its different stages. Especially when it comes to more sophisticated research questions that demand statistical analysis; large, automated coding processes; or coding procedures that involve several coders, it might be useful to choose specific software to process the digital data at hand.

There is a wide range of Computer-Assisted Qualitative Data AnalysiS (CAQDAS) software that can be used for different types of digital content analyses. Whereas most of the common tools incorporate instruments to analyse quantitative (numeric) data as well as qualitative data (e.g., MAXQDA, QDAMiner, ATLAS.ti, Qualrus, NVivo), the range of the analytical features varies. Some of the programmes offer basic dictionary-based text analysis (that enables adding codes and hierarchies to text segments); others also allow for analysing audio, video, and other non-textual data. Although using CAQDAS software for Twitter research is not the most widely used approach, it can in fact make a content analysis more efficient, and thus provide alternatives to using automated approaches when dealing with larger datasets.[1] A well-organised coding scheme can handle extensive lists of codes and categories to be applied to the material, as well as a large number of statistical procedures. If multiple coders analyse the same data, simultaneously or at different times, CAQDAS software can be used to determine intercoder or intracoder agreement.

In this chapter, we will discuss speech act analysis of tweets as an example of software-assisted content analysis. We start with some elementary thoughts on the challenges of the collection and evaluation of Twitter data before we give a brief description of the potentials and limitations of using the software QDA Miner (as one typical example for possible analysis programmes). Our focus will lie on analytical features that can be particularly helpful in speech act analysis of tweets.

SAMPLING DATA IN TWITTER

One of the great challenges in analysing Twitter data—not only in content analysis—is to choose a sample that is appropriate to answer a research question. Collecting an exhaustive sample or a true random sample is hardly, if ever, possible in terms of scraping the required data in a consistent manner (Bruns & Liang, 2012). Limited access to the Twitter API, as well as specific hardware requirements, often prevent researchers from collecting a representative sample of all Twitter users, let alone identifying and collecting an entire population of postings or users (see Gaffney & Puschmann, Chapter 5 in this volume). As long as researchers are not granted direct access by Twitter, the data-scraping process is restricted. Nonetheless, open-source tools such as yourTwapperKeeper allow collecting tweets from the search API and the streaming API (Bruns & Liang, 2012). To decide which sample should be collected for an analysis, the researchers should familiarise themselves with possible collection criteria. Content-based samples can, for example, be selected by collecting tweets that contain certain hashtags, words, or phrases. When it comes to event-related discourses, hashtags can be used for both labelling and identifying relevant postings. Tracking tweets that contain certain hashtags is a way "to establish a dataset of the most visible tweets relating to the event in question" (Bruns & Liang, 2012). The same applies for hashtags as topical markers. However, not every posting contains a hashtag, and researchers should always be aware of the incompleteness of a sample based on hashtags, words, or phrases.

Alternatively, a sample can be created by collecting tweets from a specific account. However, Twitter limits the number of postings one can scrape from a users' account. Only if the total number of sent messages is below the current API limit, which is changed off and on, is it possible to collect all tweets sent by a user. In order to track account-related conversations, it is necessary to additionally collect tweets that are addressed to an account by using @replies. A third dimension that has to be considered in sampling Twitter data is that of time. Collecting a consistent random sample within a specific time frame is virtually impossible because of the API restrictions. Nevertheless, an appropriate scraping period must be chosen to build up a data set, besides applying word-based or account-based criteria. Again, depending on the research question, one might, for example, collect a few hashtag-based postings over a longer period of time, a large number of word-based postings over a short period of time, or postings from a specified account over a long period of time. Bruns and Liang (2012) provide deeper insights into ways of collecting Twitter data.

When performing content analysis on Twitter data, tweets can be regarded as single sampling units (cf. Krippendorff, 2004, pp. 98–99). In principle, defining a tweet as the sampling unit follows clear-cut formal means (syntax): a posting, restricted to 140 characters, sent by a unique user at a particular moment; but, except for a few cases, tweets can usually also be regarded as units of meaning (semantics). Considering tweets as sampling units allows for a metadata-per-tweet approach by which metadata like account name, timestamp, geo coordinates (if provided), etc. are distinctly assigned to each tweet.

SPEECH ACT ANALYSIS OF TWEETS WITH CAQDAS SOFTWARE

CAQDAS tools allow for combining automated (quantitative) with manual (quantitative or qualitative) content analysis. It is often appropriate to identify noticeable patterns and structures of the metrics of the data. This can be achieved by measuring the number of tweets from a particular user or group of users (*metrics per user*), analysing the Twitter communication over a certain period of time (*metrics per time frame*), or the development of a given topic (*metrics per hashtag*; see Bruns & Stieglitz, Chapter 6 in this volume; Bruns & Burgess, 2012). Peaks in patterns of communication (e.g., significantly more or less tweets containing a certain hashtag in a given time frame) or distinctive features within a user's tweeting style (e.g., changing retweeting or linking habits) can be the (exploratory) basis for formulating specific research questions and hypotheses, and give the researcher an idea of where to start with a qualitative, more in-depth analysis.

In the following, we give a short outline of some of the possible (first) steps of a tweet analysis carried out with the help of a CAQDAS tool, QDA Miner. By describing some of the possible analytical processes with this particular tool, we do not necessarily consider these options to be the best way of using it. Usually, there are several ways of approaching one task within this software—or there may be better ones with another programme. However, we think that QDA Miner, as rather typical CAQDAS software, is not only a fairly comprehensible, but also a suitable tool to analyse the content of tweets. In our discussion, we thus refer to QDA Miner as a token of content analytical software.

We start with some basic settings, and end with a more detailed description of speech act analysis within the methodological framework of content analysis.

BASIC CONTENT ANALYSIS (FIRST-LEVEL ANALYSIS)

The computer-assisted content analysis of tweets can be organised on two levels. The first level allows for a basic content analysis suitable for big and small data. Basic analytical functions are word- or phrase-frequency analyses, keyword-in-context lists (KWIC), and some basic data visualisations, such as hierarchical word tree diagrams. Word-frequency lists help provide a quick overview of the words or phrases that occur in the analysed text a certain number of times. Such frequency lists can also be customised by excluding inappropriate terms (e.g., common strings like "www", "http", "RT", etc., or the (key)word that occurs in every tweet because it was the criterion for selecting the data). QDA Miner also facilitates first-level computational coding of the imported tweets. Here, character strings are lemmatised, i.e. shortened to their word stem, in order to assign inflected word forms to dictionary entries. Such automated content analysis is limited to a dictionary with fixed thesauri implying a complex, but rather static and thus superficial relation between words and meanings, as illustrated by the following example:

> As an example, the Linguistic Inquiry and Word Count (LIWC) dictionary maps the word set {ashes, burial*, buried, bury, casket*, cemet*, coffin*, cremat*, dead, death*, decay*, decease*, deteriorat*, die, died, dies, drown*, dying, fatal, funeral*, grave*, grief, griev*, kill*, mortal*, mourn*, murder*, suicid*, terminat*} to LIWC category 59, death. The asterisks are 'wild-card' characters telling the program to treat 'cremating', 'cremated' and 'cremate', as all matching cremat*, and thus all mapping to category 59. (Lowe, 2003, p. 2)

One problem with the automatic categorising is that misspelled words or chat language (e.g., "rotfl", "lol", etc.) are usually not classified in standard dictionaries. However, applying a user-defined dictionary where new words and expressions can be entered may solve this problem.

Another problem is the correct allocation of identified words for one category and their contextual meaning. Both can differ: whereas the software may categorise the word *play* under HUMOR, it actually does mean something else in the context of the tweet, "there is a video link on the page, play it." Another example is the ambiguity of the word *beat* that may be automatically classified as AGGRESSION (e.g., by the RID.CAT-dictionary), but can have another connotation in the context of "Obama beat Romney in the general election." These examples illustrate limitations of automated content analysis. Researchers should not solely rely on existing dictionaries and mere statistical frequencies, but need to carefully scrutinise these first-level findings and consider manual coding.

SPEECH ACT ANALYSIS (SECOND-LEVEL ANALYSIS)

The bigger the data set, the more difficult it gets to analyse it in-depth. After frequency counts on the first level, coding of the tweets takes place on the second. Coding means categorising text fragments or multimedia content. Categories are defined in a coding scheme. They can be generated deductively from an existing theory or inductively "as near as possible to the material" (Mayring, 2000, p. 2). However, most coding schemes are being developed in a more iterative and cyclic process (Teddlie & Tashakkori, 2010), constantly refining categories considering the pertinent, theoretical literature and the material coded so far. Annotating text segments with codes means interpreting and quantifying these segments in order to make them computable. As our focus in this chapter lies on coding speech acts in tweets, we will briefly introduce speech-act theory before giving some examples of how CAQDAS software can help with the manual coding process.

The linguistic evaluation of tweets can be quite challenging due to possible grammatical inconsistencies of computer-mediated language. As Twitter is widely used for conversation (Bruns, 2012; Magnani et al., 2011), an analysis of speech acts is highly interesting, as it can give information about the types of actions that people want to accomplish through communication (Nastri, Peña, & Hancock, 2006). The objective of a speech act analysis is to identify different types of purposeful utterances, such as command, complain, compliment, etc. There are several taxonomies categorising speech acts with regard to their intention (illocutionary acts). Often, Searle's (1976) basic classification of illocutionary acts, which again is based on Austin's (1962) work, is adopted for analysing computer-mediated language (e.g., Nastri et al., 2006). Searle (1976) categorised purposeful utterances as assertives or representatives (commiting the producer of an utterance to the truth of the proposition), directives (attempting to get the receiver to do something), commissives (commiting the producer to some future course of action), expressives (expressing the psychological state of a situation), and declarations (bringing about a change in a state of affairs). Table 8.1 gives some examples of possible verb groups for each category.

Table 8.1: Basic Classification of Illocutionary Acts (Purposeful Speech Acts) by Searle (1976)

Speech Act	Paradigms of Verbs (Examples)
Assertive / representative	Describe, call, conclude, deduce
Directive	Ask, order, command, request, beg, invite, permit
Commissive	Promise, swear
Expressive	Thank, congratulate, apologise, condole, welcome
Declaration	Declare, nominate

While discussing Searle's theory in more depth is beyond the scope of this chapter, it should have become clear that analysing speech acts in Twitter communication demands a lot of interpretative effort, and may not be possible without some theoretical considerations. One difficulty lies in the linguistic specifics of tweets. For example, the researcher needs to specify if a hyperlink can be identified as a speech act. One could regard a hyperlink as an implied request to click on it and code it as directive. However, if codes are supposed to give information about the meaning of the material, this would probably not be really helpful. It could instead be reasonable to explore the content behind the hyperlink and code it in a way that appropriately determines the underlying speech act. If one is instead merely interested in the structure of a tweet, the hyperlink could simply be coded as such (the same procedure can be applied to the other Twitter-specific signifiers, i.e. the @-symbol, RT, or #, in order to quantify these functional operators, cf. Thimm, Einspänner, & Dang-Anh, 2012).

A similar decision must be made in the case of chat language (or rather, Internet slang), especially emoticons. Sometimes one tweet only consists of a slang utterance, e.g. "lol", or just a smiley. This could point to some form of humour or self-expression (Nastri et al., 2006). Here, the traditional speech-act classification may not be sufficient. It could therefore be reasonable to consider creating a new category (and a new code) for these or similar cases of Twitter language. Sometimes speech-act categories can also overlap, i.e. directives and commissives. This makes determining the "right" speech act even more difficult, especially if several coders work on the same material and individual intuitions have be harmonised to assure consistent coding decisions.

Most of these difficulties cannot be resolved by computer software, as they are inherent to the data or require theoretical evaluation. However, using content-analysis software has the advantage that codes and labels can be modified or merged at any time. It can be helpful to use a "work in progress" category in the beginning of the coding process, for example, if the rules for distinguishing speech acts are not yet defined conclusively. However, any final decision on the definition of the categories must be explicated in the coding scheme as clearly as possible. Based on the coding of speech acts, CAQDAS software can run correlations on different speech-act codes in order to identify argumentative patterns in Twitter communication. One result may be, for example, that in a high number of cases assertives co-occur with commissives, or that expressives contain a high number of emoticons (if coded respectively). Such results can then again be statistically correlated with different variables—for example, a groups of users—in order to find out how certain social groups use which kind of linguistic strategies or argumentation patterns on Twitter. This way of analysing the language of Twitter is one of the most useful features of content analysis software. At the same time, however, statistical parameters such as correlations may be difficult to interpret, and researchers need to decide which analytical procedures can be meaningfully applied in light of their hypotheses or research questions, to avoid drawing artificial, data-centric conclusions.

CONCLUSION

Content analysis provides a useful and multifaceted, methodological framework for Twitter analysis. CAQDAS tools support the structuring of textual data by enabling categorising and coding. Depending on the research objective, it may be appropriate to choose a mixed-methods approach that combines quantitative and qualitative elements of analysis and plays out their respective advantages to the greatest possible extent while minimising their shortcomings. Big data (from several thousand up to millions of tweets) should rather be considered for a quantitative assessment of, for instance, communication patterns within the data set. It can subsequently be reasonable to extract a subsample (= small data) and analyse it qualitatively with the help of CAQDAS software. Basic functions such as word, phrase, or category count analyses as well as features like co-occurrence or KWIC-analyses can be useful additions for a systematic interpretation of the data. The process of coding speech acts within tweets as a form of qualitative content analysis can be very demanding, as (re-)contextualising tweets, differentiating similar speech acts (or topics, arguments, etc.), categorising Twitter-specific symbols, and finally, interpreting the co-occurrences can be quite challenging. Table 8.2 summarises the main advantages and limitations of CAQDAS in Twitter analysis.

Conducting content analysis with the use of CAQDAS software can expand the researcher's capability to interpret Twitter data. However, due to various limitations, qualitative data analysis software should rather be used as a supportive tool than a product that drives the whole research process. In the end, the interpretation of the findings still has to be done by the researcher.

Table 8.2: Overview of the Advantages and Disadvantages of Using CAQDAS Software for Analysing Twitter Messages

CAQDAS and Twitter Analysis: Advantages	CAQDAS and Twitter Analysis: Disadvantages
Allows for mixed-methods approaches.	CAQDAS packages are very complex; need a lot of time and effort to get to know the particular features and functions.
Metrical analyses as well as frequency analyses can be carried out quickly; give a good first impression on the data.	Dictionary entries/categories not sufficient for language-in-context.
Basic analysis (word/phrase/category count) and visualisation possible with small and big data.	Limited automated coding processes; manual coding required.
Codes can be arranged hierarchically and be modified during coding and analysis; overlapping of codes possible.	In-depth content analysis (semantic analysis) hardly possible with big data.
Inter- and intracoder reliability tests can be performed.	Most software is proprietary and costly.

NOTE

1 More information on CAQDAS can be found, for example, on the website of the Surrey CAQDAS networking project (http://caqdas.soc.surrey.ac.uk).

ACKNOWLEDGMENTS

This chapter originates from the context of the research project "Political Deliberation on the Internet" (as part of the DFG SPP 1505 "Mediatized Worlds"), headed by Caja Thimm, University of Bonn, Germany. We would like to thank the German Research Foundation (DFG) for funding our work.

REFERENCES

Austin, J. L. (1962). *How to do things with words*. Oxford, UK: Oxford University Press.

Berelson, B. (1952). *Content analysis in communication research*. New York, NY: Free Press.

Bruns, A. (2012). How long is a tweet? Mapping dynamic conversation networks on Twitter using Gawk and Gephi. *Information, Communication & Society*, *15*(9), 1323–1351. doi:10.1080/1369118X.2011.635214

Bruns, A., & Burgess, J. (2012). *Notes towards the scientific study of public communication on Twitter*. In A. Tokar, M. Beurskens, C. Puschmann, S. Keuneke, M. Mahrt, I. Peters, . . . Weller, K. (Eds.), *Science and the Internet* (pp. 159–169). Düsseldorf, Germany: Düsseldorf University Press.

Bruns, A., & Liang, Y. E. (2012). Tools and methods for capturing Twitter data during natural disasters. *First Monday*, *17*(4). Retrieved from http://firstmonday.org/htbin/cgiwrap/bin/ojs/index.php/fm/article/view/3937/3193

Capurro, R., & Pingel, C. (2002). Ethical issues of online communication research. *Ethics and Information Technology*, *4*(3), 189–194.

Herring, S. C. (2010). Web content analysis: Expanding the paradigm. In J. Hunsinger, L. Klastrup, & M. Allen (Eds.), *International handbook of Internet research* (pp. 233–249). Dordrecht, The Netherlands: Springer.

Huang, J., Thornton, K. M., & Efthimiadis, E. N. (2010, June). *Conversational tagging in Twitter*. Paper presented at the 21st ACM Conference on Hypertext and Hypermedia (HT '10). Retrieved from http://jeffhuang.com/Final_TwitterTagging_HT10.pdf

Jansen, B. J., Zhang, M., Sobel, K., & Chowdury, A. (2009). Twitter power: Tweets as electronic word of mouth. *Journal of the American Society for Information Science and Technology*, *60*(11), 2169–2188.

Krippendorff, K. (2004). *Content analysis: An introduction to its methodology*. Thousand Oaks, CA: Sage.

Kumar, A., & Sebastian, T. M. (2012). Sentiment analysis on Twitter. *International Journal of Computer Science Issues*, *9*(4), 372–378.

Lowe, W. (2003). Software for content analysis—A review. Retrieved from http://www.ou.edu/cls/online/lstd5913/pdf/rev.pdf

Magnani, M., Montesi, D., Nunziante, G., & Rossi, L. (2011). Conversation retrieval from Twitter. In P. Clough, C. Foley, C. Gurrin, G. J. F. Jones, W. Kraaij, H. Lee, & V. Murdoch (Eds.), *Advances in information retrieval* (pp. 780–783). Berlin, Germany: Springer.

Mayring, P. (2000). Qualitative content analysis. *Forum: Qualitative Sozialforschung / Forum: Qualitative Social Research*, *1*(2), Article 20. Retrieved from http://nbn-resolving.de/urn:nbn:de:0114-fqs0002204

Nastri, J., Peña, J., & Hancock, J. T. (2006). The construction of away messages: A speech act analysis. *Journal of Computer-Mediated Communication*, *11*(4), 1025–1045.

Nielsen, A. (2011). *A new ANEW: Evaluation of a word list for sentiment analysis in microblogs*. Paper presented at the Extended Semantic Web Conference, Workshop Making Sense of Microposts (#MSM2011), Heraklion, Crete. Retrieved from http://sunsite.informatik.rwth-aachen.de/Publications/CEUR-WS/Vol-718/paper_16.pdf

Rössler, P. (2002). Content analysis in online communication: A challenge for traditional methodology. In B. Batinic, U. D. Reips, & M. Bosnjak (Eds.), *Online social sciences* (pp. 301–317). Seattle, WA: Hogrefe & Huber.

Searle, J. R. (1976). A classification of illocutionary acts. *Language in Society*, *5*(1), 1–23.

Teddlie, C., & Tashakkori, A. (2010). Overview of contemporary issues in mixed methods research. In A. Tashakkori & C. Teddlie (Eds.), *Sage handbook of mixed methods in social & behavioural research* (pp. 1–41). Thousand Oaks, CA: Sage.

Thimm, C., Einspänner, J., & Dang-Anh, M. (2012). Twitter als Wahlkampfmedium: Modellierung und Analyse politischer Social-Media-Nutzung [Twitter as a medium in election campaigns: Model and analysis of the political use of social media]. *Publizistik*, *57*(3), 293–313.