

Twitter data analysis as contribution to strategic foresight-The case of the EU Research Project “Foresight and Modelling for European Health Policy and Regulations” (FRESHER)

André Uhl¹  · Nina Kolleck² · Edgar Schiebel³

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Abstract In this article the value of Twitter data analysis for a strategic foresight exercise is discussed. The article offers an overview of Twitter’s basic functionalities, previous Twitter research and related studies on using Twitter in foresight projects to date. Based on this knowledge the case of the EU research project “Foresight and Modelling for European Health Policy and Regulations”(FRESHER) is used to conduct a Twitter data analysis in three steps: an analysis of web-links to get insights into the content spread via Twitter, a social network analysis to define central actors in a Twitter debate, and a hashtag-analysis to find out which topics are discussed and to support the identification of drivers of noncommunicable diseases. The article shows the benefit a Twitter data analysis provides for the FRESHER project and reveals implications for future research in this field.

Keywords Foresight · Twitter · Horizon scanning · Network analysis · Policy · Governance

Introduction

Online social media platforms such as Twitter, Facebook or Youtube cover a big share of the world wide digital communication today. Different software tools allow the gathering of information about users and the collection of data about their communication behavior. Especially the microblog Twitter provides manifold opportunities in data analysis thanks to its functionality and the availability of appropriate software. Despite these opportunities and a wide range of studies about the use of Twitter for different disciplines, the analysis of Twitter data and its contextualization within the scope of Foresight projects is rarely discussed in scientific literature. Therefore the author of this article asks: Can a Twitter data analysis contribute valuable input to a strategic Foresight exercise?

In order to answer this question the case of the EU research project “Foresight and Modelling for European Health Policy and Regulations” is used,¹ which is part of the EU research and innovation program Horizon 2020.² An international consortium of ten European research institutes conducts this project by applying a cross-disciplinary approach. The objective of FRESHER is to explore alternative futures for the European health sector in order to test the efficiency of different options to tackle the burden of non-communicable diseases (NCDs). The study presented in this article examines whether Twitter data analysis can contribute valuable results to:

- the gathering of relevant information around the theme,
- the search for contacts and possible participants for workshops or interviews,

✉ André Uhl
mail@andreuhl.de

Nina Kolleck
n.kolleck@fu-berlin.de

Edgar Schiebel
edgar.schiebel@ait.ac.at

¹ Böckhstraße 49, D-10967 Berlin, Germany

² Habelschwerdter Allee 45, D-14195 Berlin, Germany

³ Donau-City-Straße 1, A-1220 Vienna, Austria

¹ <http://www.foresight-fresher.eu>.

² The EU Framework Programme for Research and Innovation: <http://ec.europa.eu/programmes/horizon2020/>.

- the identification of drivers with potential impact on the development of NCDs in the future.

The article is structured as follows: Subsequent to the introduction the main characteristics and functionalities of Twitter are described, an overview of previous Twitter research is provided and possible opportunities emerging with the use of Twitter for strategic Foresight are shown. Then the FRESHER research project is briefly described and possible points of action for a Twitter data analysis within this project are shown. Based on this the methodological approach of the study is explained, followed by the presentation of the findings. Finally, the results are discussed, a conclusion is drawn and possible implications for future work in this research area are revealed.

Twitter

Development, characteristics and user

What is twitter?

Twitter was created in March 2006 under its original name “Twtr”. Since co-founder Jack Dorsey posted the first message (“just setting up my twtr”) Twitter has developed to the most used and known microblogging platform and one of the most popular online social networking services. At the beginning of 2010 the site had 20 million unique users and 50 million messages per day. By March 2015 these numbers had grown to 302 million unique users and 500 million messages, better known as tweets, were being sent.³ Today, the platform can be regarded as a “... communication phenomenon whose reach is still growing and whose consequences are far from understood” [30].

Like other microblogs Twitter can be described by the following five key characteristics [12]: (1) a concept of shortness, due to the limitation of 140 characters for each post (hence the name *microblog*), (2) a concept of friends (the various accounts a user follows) and followers (the accounts that follow a user), (3) a concept of information presentation, where messages of friends are presented in a list with the most recent at the top, (4) a concept of openness (users can set their profiles to private, but that is rather unusual; almost all posts on Twitter are public), and (5) a concept of web services, meaning that Twitter allows third-party applications to connect with the service using an open application programming interface (API). This open API “provides a mechanism to make use of the functionality of a set of modules without having access to the source code or a specific license” [2] and is therefore crucial in order to conduct a Twitter data analysis by any

means. In view of these characteristics, a microblog, with Twitter being its most prominent representative, can be classed as a service for a complete new way of communication.

How does twitter work?

Besides the basic function of posting a Twitter message (called “tweet”), and the possibility to follow and be followed by other users, Twitter provides several other specific features. Three of these are “replies”, “mentions” and “retweets”. Replying to a user by starting a tweet with an @ sign followed by the user name (@user) makes it possible to address a user directly via the public Twitter feed. To mention another user, works in a similar way; it also includes @user but not at the beginning of a tweet. The difference is that a reply is directed to the other user and therefore seen by him or her, while a mention is not directed at the user. You could also say a reply is a message *for* someone while a mention is a message *about* someone [20]. By using the retweet function a user spreads the original message from another user by resending it. While mentioning is a way of referring to another user without necessarily sharing the same opinion, a retweet can be seen as an informal recommendation of a message that another user finds important, interesting or at least entertaining. Therefore the retweet function is a key mechanism for information diffusion and raising content visibility on Twitter [36, 47].

Another key function of Twitter is the use of “hashtags”. Putting a “#” (hash) sign in front of a certain word is a simple way of adding context to a message. This can be a name (e.g. #obama), an event (e.g. #election2016), a movement (#refugeeswelcome), a conference (e.g. #futuresconference2015) or anything else. By adding a hashtag to a Tweet, the referred word receives the informal function of a topic. Thus, hashtags are helpful when sharing news, knowledge or general contributions to a certain topic, and to spread information across networks of interest. Conversely, hashtags make it easy to search and collate information, discussions or central actors regarding a specific theme [10, 37]. Also, hashtags can be especially useful when Twitter is used as a communication platform, for example during a conference to share ideas, impressions, comments and additional materials on a “#channel” [11].

While each tweet can be retweeted, be addressed to other users by replies, or relate to specific context by a hashtag, information spreading on Twitter can also work in other ways: Tweets can additionally contain photos, videos with a maximum length of six seconds or additional web links. The latter is particularly interesting for Foresight practitioners who want to use Twitter as a data source, since they might refer for example to news articles, studies, or reports relevant to the theme under investigation.

³ Twitter (2015) <https://about.twitter.com/company>.

Who uses twitter and why?

With the growing popularity of Twitter, not only has the “daily chatter”, as Java et al. [28] describe it, increased but also the service’s potential as a fast information distribution platform, as a tool for coordination in disaster control/response, or as an instrument for political campaigns [30]. By the time Twitter reacted to the predominant way people used the platform and changed its initial question in 2010 from “What are you doing?” to “What’s happening?” focusing on ongoing news and events. Other changes Twitter made in reaction to the user behavior are even more remarkable: Both retweets and hashtags were first initiated by users without having a formal function to use it; this was a matter of self-initiative in order to spread information or add context to a message. Twitter later implemented these features formally, which are now two of the services’ most important functions [22].

A study from Smith and Brenner [42] gives some hints on what a “typical Twitter user” in the United States might look like. Although the results might be different considering a European sample it seems plausible to assume at least a similar demographic tendency. According to the results of the study most of the Twitter users are younger, with a higher education, more affluent showing a bigger political interest than the average. It is therefore important to note that a Twitter data analysis cannot be seen as a representative sample of a population. Such data can only provide insights in the online communication of the part of the population using this specific online service. This does not necessarily make such data less important or less interesting for social scientists or Foresight practitioners. In fact, focusing on a group that shows a relatively high level of involvement and interest in societal issues [29] might be fruitful depending on the specific topic of research.

Twitter research

Since Java et al. [24] published their paper “Why we twitter: understanding microblogging usage and communities“, one of the first studies on Twitter finished in the same year the service was launched, a growing number of studies on Twitter research has been published. According to a bibliometric analysis from Kayser and Bierwisch [31] examining the different research areas from the year 2006 until 2014 (articles and proceeding papers), the fields “Computer Science” and “Engineering” show the highest activity in Twitter research while other disciplines like “Business and Economics”, “Communication”, “Education”, “Psychology” and “Social Sciences” also show a noteworthy number of contributions. However, the boundaries of the different research areas are not always as clear since some of the studies follow an interdisciplinary approach, while others use case studies from a certain discipline to make a point. Some studies from different

disciplines that received attention in the scientific community shall be mentioned in the following.

From the beginning of Twitter research a significant number of studies examined the use of Twitter in a political context. While some try to grasp the role of the microblog in political protest movements [30, 38], others try to yield insights into political opinions via semantic structures in Tweets [41], by sentiment analysis [21] or through a mixed-method approach of social network analysis and keyword analysis [23]. However, expectations that Twitter might work as a tool to predict electoral results could not be fulfilled since Twitter users are neither a representative sample of the population [40] nor do tweets necessarily reflect real life electoral behavior [26].

Jungherr and Jürgens [25] also discuss the potential of forecasts based on Twitter data. Instead of aiming to predict events by identifying typical data patterns they suggest to model the “normal state” of a system. Differences between this model and empirical data should then work as an indicator for the occurrence of extraordinary events. Other studies cover geographic aspects of Twitter use [14], examine the influence of distance, national boundaries or language on Twitter’s social ties [45], or focus on the use of Twitter as a tool for educational purposes [18, 19] and as communication tool at scientific conferences [10, 11, 13, 37].

Some follow a rather broad approach, analyzing how communication flow on Twitter works in general. Unsurprisingly, such studies were often conducted in the field of “Computer Science”. Castillo et al. for example focus in their studies on the analysis of newsworthy information [6] and later on information credibility [7] on Twitter to establish an automatic discovery process of relevant and credible news. Weitzel et al. [47] have a similar goal utilizing social network analysis to assess reputation from source information in the medical domain. They tested a method to rank trustworthy sources on the basis of a retweet network and concluded, that in the Twitter community trust plays an important role in spreading information. Li et al. [29] also reveal the efficiency of information diffusion on Twitter and the specific user behavior leading to such information diffusion.

Unlike numerous attempts at using Twitter for forecasting or the “prediction” of the future (e.g. electoral results, product sales or stock markets developments), which have been controversially discussed [15, 30, 40], there have only been few attempts to examine the use of Twitter in the field of Foresight and futures research. In the following the author takes a closer look at some related studies on Twitter and Foresight. Thereafter it is tried to identify opportunities where Twitter may be used as an instrument for strategic and participative Foresight.

Twitter and foresight

The number of studies investigating the use of Twitter for Foresight is still limited and only a handful of papers describe

efforts to apply the online platform for different purposes so far. For example Pang [34] presents an approach he calls “social scanning” whereby he aggregates online content from futurists and Foresight practitioners. This process of gathering and filtering content from Twitter and other social media platforms shall help to identify trends and “weak signals” for possible future developments. One could criticize the approach for drawing exclusively on content from futurists, which might already be shaped by pre-assumptions these persons have about the future.

Amanatidou et al. [1] implement Twitter into a horizon scanning framework for the European project “Scanning for Emerging Science and Technology Issues” (SESTI). While the authors use the platform mainly for collecting web-links they also emphasize Twitter’s potential for detecting “weak signals” as well as the opportunity to use the microblog as communication instrument during a Foresight process. However, the comprehensive horizon scanning framework was the focal point of the study. Twitter was one information source amongst many and in this regard used as an additional element to complement the framework. Schatzmann et al. [39] give an overview of methods in a field they define as “Foresight 2.0”. They discuss the aptitude of Twitter and other web 2.0 applications for foresight exercises and outline a possible evaluation process of digital applications by their intended use, knowledge generation and quality of results.

Raford [35] explores the role online services like Twitter could play in scenario planning. He thus compares five empirical case studies. Like Amanatidou et al. Raford emphasizes both the potential Twitter holds for a horizon scanning process and the opportunities it could offer in communication and in promoting a public dialog. He points out that research communities exploring online data are still largely separated from scenario planning and public engagement, and argues for the potential value of real-time online systems and the interaction with other instruments in a scenario process.

One of the first studies focusing exclusively on the use of Twitter in Foresight comes from Kayser and Bierwisch [31], asking how the online service can be used as an integral part in technology foresight. The authors examine the potential of Twitter as a tool for monitoring an ongoing debate on the “quantified self” phenomena, but also tests Twitter’s aptitude as a tool for engagement in a foresight exercise. Some of the main assets of Twitter emphasized by the authors are the broad variety of content delivery, the fast access to a large number of people and the possibility to receive real-time feedback on ideas. They suggest working with a mixed methods approach instead of using Twitter as the only data source for a Foresight project.

The study in this article builds on the attempts and insights described in the previous studies. Likewise, the author sees great potential of Twitter as an additional instrument in different phases of strategic Foresight exercises. There are several

perspectives in the literature of how many phases of Foresight should be classified and how to differentiate these phases [3, 8, 22]. The author of this article distinguishes four main phases of a strategic Foresight [16]: (1) Gathering and analysis of information and data, including desk research and horizon scanning, (2) generating knowledge through a participative process, usually in the form of alternative future scenarios, (3) formulating options and handing over of policy recommendations, and (4) implementation, communication and dissemination of results. The previous studies and the way Twitter works as an online communication service speak for Twitter as a useful instrument at all phases: As a tool for data analysis and information scanning at the beginning of a Foresight, as communication tool during the phase of knowledge generation, and at the end for result dissemination. Furthermore it could serve as a tool for continuous monitoring on a topic over the whole Foresight process (see Fig. 1).

In this article the author concentrates on the beginning of a Foresight project. In almost every case such a project starts with desk research and the gathering of information in order to capture the status quo of a topic. Other important tasks are the identification of potential stakeholders, the search for participants of workshops or interviews, or the identification of key determinants and drivers affecting the research topic fundamentally. Foresight practitioners are usually confronted with an information gap on the topic under debate. Thus it is necessary to apply varying methods to fill this gap as good as possible. It is assumed that a Twitter data analysis based on a certain hashtag can aid work on this task and broaden the information base at the beginning of a Foresight project. In order to test our assumption the case study of the EU research project “Foresight and Modelling for European Health Policy and Regulation” (FRESHER) is used, which is described in the following chapter.

Foresight and modelling for European Health Policy and Regulations (FRESHER)

Structure, objectives and approach

Today non-communicable diseases (NCDs) such as heart disease, stroke, cancer, diabetes, depression, and others are the leading cause of mortality in Europe.⁴ Common risk factors of the major NCDs include tobacco, harmful use of alcohol, unhealthy diet, insufficient physical activity, obesity, raised blood pressure, raised blood sugar and raised cholesterol. While the number of people afflicted by NCDs is increasing and the burden is growing, the WHO underlines that a great part of the NCDs threat can be overcome by using existing knowledge, and possible solutions are highly cost-effective.

⁴ WHO (2015): <http://www.who.int/gho/ncd/en/>.

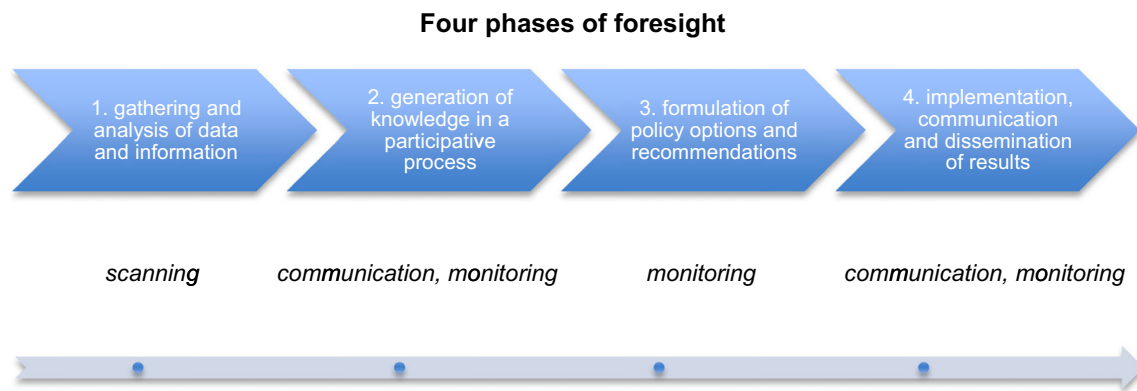


Fig. 1 Phases of Foresight and potential use of Twitter, source: adapted from Giesecke & Uhl, 2015

The research project “Foresight and Modelling for European Health Policy and Regulations” (FRESHER)⁵ draws on this knowledge to support the search for appropriate solutions. A consortium of ten international European research institutes and partners from eight different countries conduct FRESHER. It runs over a time period of three years from the beginning of 2015 until the end of 2017. The project is part of the EU research framework program Horizon 2020 and financed by the European Union Funding for Research & Innovation. According to the FRESHER Funding Frame (unpublished proposal) the overall project objective is to outline alternative futures using emerging health scenarios to test future policies to effectively tackle the burden of NCDs. Intermediary goals of the project are:

1. To produce quantitative estimates of the future burden (horizon 2030 and 2050) of NCDs in the EU and its impact on health care expenditures and delivery, population well-being, health and socio-economic inequalities.
2. To base such estimates on Foresight techniques giving credit to the interdependencies of structural long-term trends in gender relations, demographic, technological, economic, environmental, and societal factors (horizon 2050).
3. To illustrate options for decision-makers in order to contain the burden of NCDs.
4. To promote an interactive process with key actors in public health and European policies.

Following these goals the FRESHER project shall contribute to a better understanding of causal chains and risk factors of NCDs. This shall provide decision-makers with “timely, accurate information to consolidate the scientific knowledge on the effectiveness of policy interventions.”⁶ The project will also form an active network for effective policy dialogue with

major stakeholders of public health policies in Europe and give recommendations on research priorities to reduce the impact of NCDs in Europe.

Horizon scanning and twitter data analysis

Two core elements of the FRESHER Foresight process are the implementation of a horizon scanning process and the development of future health scenarios built on the results of the horizon scanning. Horizon scanning can be described as a practice integrated in the first phase of Foresight exploring trends, drivers, and challenges but also past experiences to identify topics and factors that might influence the theme under investigation in the future [32]. Delaney gives an overview of existing definitions of horizon scanning, and most of them closely resemble the goal-oriented description above [9].

Apart from this rather broad explanation of what a horizon scanning should lead to, there is no common understanding in foresight literature of how to process horizon scanning in detail, which methods should be used or which steps to be included in such a process. Some scholars underline the opportunities of automated or semi-automated horizon scanning processes, while using different software-supported and often self-developed infrastructure to process information [17, 33, 44]. Amanatidou et al. [1] describe their experiences from the European horizon scanning project “Scanning for Emerging Science and Technology Issues” (SESTI) which uses different scanning approaches and scanning tools to improve policy formulation and dialogue. Also, a number of governments operate national horizon scanning centres and have developed their own framework processing information from numerous sources in order to prepare for future challenges.⁷

In the FRESHER project the term horizon scanning is used in a comparatively broad way, meaning a general scanning of

⁵ <http://www.foresight-fresher.eu>.

⁶ <http://www.foresight-fresher.eu/en/Who-we-are/Mission-Statement/>.

⁷ see Government of the United Kingdom: <https://www.gov.uk/government/groups/horizon-scanning-programme-team>, RAHS Programme Office: <http://www.rahs.gov.sg/public/www/home.aspx>, and [43].

different sources like scientific literature, conferences, Foresight projects, online sources etc. without drawing on an existing horizon scanning framework. One key mechanism to identify determinants, trends and drivers in the context of NCDs is a semi-automated bibliometric analysis of scientific literature. Another important element is the discussion of the results with an expert committee and in further expert interviews. These interviews shall also help to explore which policies could address future challenges on NCDs.

The approach sets out from a holistic understanding of the health and well-being sector. Social factors such as family and networks influence health and well-being just as well as economic factors such as the standard of living, environmental factors such as pollution and climate change, and also the safe and secure surrounding in which a person lives. Therefore the horizon scanning looks also at the external factors that lie outside a narrow definition of the health system. The results of the scanning process lay basis for of the scenario building later on.

The aim of this study is to examine whether a particular hashtag on Twitter might serve as a valuable search tool to find relevant information on the topic of NCDs, to identify experts in the field of NCDs, and as an instrument to complement the identification of determinants and drivers for NCDs. Therefore the following three research questions are formulated:

RQ1: Do messages with the hashtag #ncds contain thematically relevant web-links?

RQ2: Can central actors of a Twitter network around the hashtag #ncds be regarded as useful contacts for the foresight project?

RQ3: Do Tweets with the hashtag #ncds contain other hashtags representing determinants and drivers of non-communicable diseases?

In the following the methodological approach is described, the findings are presented and discussed, and possible indications for more research in the future are shown.

Study

Methodological approach

Every time users interact with online services they leave data traces, documenting their online behavior. While most of these traces are invisible to researchers, Twitter offers access to comprehensive data sets through its open application programming interface [25]. Beside the actual Twitter message much other information is available, e.g. the number of followers of a user, the number of his or her “friends”, or the profile description. Furthermore a set of metadata is accessible

such as geographical data (in case the Twitter user specifies his or her geographical location), the exact time a tweet was sent or the user ID. All in all, Twitter offers a publicly available, comprehensive and in large parts spatially embedded network dataset, which can be of great value for researchers [45].

Not so long ago the aggregation, analysis and illustration of data from social media platforms such as Twitter demanded significant programming and advanced data management skills [20]. Today different software applications deliver pre-structured data sets by connecting to the Twitter application programming interface. This enables researchers to concentrate mainly on measurement, analysis and interpretation of data, instead of spending time with coding or mastering an appropriate research tool. For this study the program NodeXL was used. The software runs on Windows operating system and is an add-on for the program Microsoft Excel, where it is virtually integrated as an additional tab while all other Excel functions can still be used for the dataset.

By using the import function for Twitter data NodeXL provides search results as structured network information in different spreadsheets. The “Edges” spreadsheet (relationships between Twitter users are represented as network edges) includes information on messages sent within this network, while the “Vertices” spreadsheet (Twitter users are represented as network vertices) includes information on each user within this network. The search is limited to a maximum amount of 18.000 tweets and also to a time period seven days back from the present. If more data is required a regular search has to be done over a longer time period.

For the study a Twitter network is examined, consisting of all users who include the hashtag #ncds in their Tweets or who are mentioned in such a Tweet from July 5th to September 7th, 2015. Tweets containing the hashtag #ncds are imported every week within this time period. The decision to focus the search on a hashtag instead of a keyword was made because of the specific function of hashtags as described earlier in chapter 2.1. Concentrating on a hashtag makes it easier to capture messages on a specific theme. When a user decides to include a hashtag in his/her tweet he/she adds context to the message and in this regard contributes consciously to a public (Twitter) dialogue on a certain theme. The author’s goal was to aggregate tweets and information about users who deliberately take part at a public dialogue by using a certain hashtag.

Defining the most appropriate hashtag for the search required a pre-analysis of tweets. As Bruns and Stieglitz [5] point out “hashtag research depends crucially on the existence of a widely adopted hashtag, and on its (early) detection and tracking by researchers”. This is especially true for a thematic field like “non-communicable diseases” where different terms or abbreviations, and therefore alternative hashtags, might be used unlike for example in the case of #smartgrid where the choice of the hashtag term is obvious. To make sure it was searched for the most common hashtag used in the Twitter

debate on non-communicable diseases, tweets containing different hashtags (*#ncd*, *#ncds*, *#noncommunicable*, *#noncommunicablediseases*) were imported over a time period of two months. Based on the number of tweets and a spot check of the content *#ncds* was identified as the most common hashtag in this context; thus it was decided to focus on this search term.

In every Twitter data analysis the question of how to deal with retweets must be answered. There can be different ways how to interpret retweets depending on the research question and the goal of investigation [26, 27]. In this study the author wants to examine which web-links are shared the most, which users get the most attention and which hashtags are dominant in the Twitter debate of NCDs. Retweets are interpreted as contributing elements to this debate with the same importance as “original” tweets. Therefore it was decided to give all messages in the network the same attention, no matter if they are “original” tweets or retweets.

The study in three steps

The study is divided into three major steps:

1. In the first step web-links included in the tweets of the dataset are examined. The total number of web-links is counted and the ten most shared links in the network are checked more precisely regarding the included information. These web-links are then categorized in terms of the character of the included information, for example news, reports, scientific studies, or advertisement/public relation. This allows an assessment whether the shared links can be seen as a valuable contribution to the Foresight exercise or not, and whether these links help to broaden the information base or not. On this basis *RQ1* is answered: *Do messages with the hashtag #ncds contain thematically relevant web-links?* Furthermore the examination of web-links provides a first overview of the topics dominating the debate on NCDs on Twitter within this time period.
2. In the second step of our study a social network analysis of Twitter users in the dataset is conducted. This builds the basis for answering *RQ2*: *Can central actors of a Twitter network around the hashtag #ncds be regarded as useful contacts for the Foresight project?* The Vertices represent all Twitter users within this network. This implies users who include the hashtag *#ncds* in their tweet as well as users who are mentioned in a Tweet which includes *#ncds*. Edges represent relationships of Twitter users within this network. The Twitter API provides three types of relationships/messages: (1) „Tweets“, meaning a user has tweeted without mentioning another user, represented by a self-loop. (2) “Replies to”, meaning a user replies to another user by mentioning him or her at the beginning of the tweet. (3) “Mentions”, meaning a user mentions another user within the tweet. “Mentions” also include retweets, as NodeXL classifies retweets as a certain form of mentions.
3. In the third and final step of the study the hashtags included in tweets from the network are analyzed. This aims to answer *RQ3*: *Do Tweets with the hashtag #ncds contain other hashtags representing determinants and drivers of non-communicable diseases?* In order to answer this question the hashtags are compared to a list of determinants and drivers of NCDs, identified on the basis of the bibliometric analysis of scientific articles that was conducted within the horizon scanning process of the FRESHER project, and based on the feedback of the expert committee. Furthermore it is examined which hashtags are most frequently mentioned. In addition to the examination of the web-links this helps answer the overall question of which topics dominate the Twitter debate on NCDs within the defined time period.

Findings

For this study data were imported from the Twitter search network with the search term *#ncds* every week from July 11th, 2015 over a time period of eight weeks to September 7th, 2015. The received dataset contains Twitter data from July 4th, 2015, 04:51 pm, to September 7th, 2015, 09:03 am, with a total number of 3.656 Twitter messages. 5.088 edges represent the total number of relationships in the network: „Tweets“(759 edges), “Replies to” (50 edges), and “Mentions” (4.278 edges). As described previously, “Mentions” include retweets which are by far the most often form of messages/relationships in the dataset (3.502 edges). In

the following the term “edges” is used when describing all three types of relationships in the dataset.

Step 1: analysis of web-links

The dataset contains 820 different web-links that are spread via 3.694 edges within the network. Table 1 shows the website headers of the ten web-links with the highest counts. The most shared link leads to the website of the CDC Centers for Disease Control and Prevention (the American health protection agency), more precisely to the web page featuring the current CDC newsletter. The second most shared link leads directly to this newsletter in PDF format, followed by a web-link that leads to a news article on *Barbados Today* about a new tax on sugary drinks. This tax was introduced in Barbados on August 1st to reach lower sugar consumption, a political instrument that was discussed in other countries, too. The 4th link leads to the website of a company offering services to support health professionals and patients with exercises and the management on NCDs. The 5th web-link leads to a BBC news article also contributing to the discussion on tax on sweet drinks, while the 6th leads to a report of the British Medical Association on promoting healthy diets among children and young people, released in July 2015. The 7th leads to a scientific article in PLOS Medicine Journal on the global spread and disparity of NCDs, the 8th to an article about challenges in the tackling of NCDs on the website of the Clinton Foundation, and the 9th to an article about financing the fight against NCDs on the website of DEVEX, a media platform for global development. The last of the ten web-links leads to Innovation Countdown 2030, an initiative to identify, evaluate, and showcase technologies and interventions to transform global health by 2030. The initiative

is supported by the Norwegian Agency for Development Cooperation, the Bill & Melinda Gates Foundation, and the US Agency for International Development.

Three of these top ten links can be classified as reports of governmental initiatives (1, 2 and 6), three are reports or articles of non-governmental organizations and private initiatives (8, 9, 10), two articles from genuine news websites (3, 5), one article from a scientific journal (7) and another one leads to a commercial website (4). Most of them contain more links to further information such as news around NCDs (5, 6, 9), scientific articles or studies (1, 2, 6, 7, 8) or contacts to professionals in different fields of NCDs (1, 2, 4, 6, 7, 10). In fact, the web-link leading to the report of the initiative Innovation Countdown 2030 provides a collection of information with a close connection to the overall goal of the FRESHER project: the identifications of technologies and interventions that can be seen as possible drivers to shape global health by 2030. In summary, and as an answer to *RQ1*, it can be said that the top ten web-links contain up-to-date information on the thematic complex of NCDs and contribute valuable insights to the scanning process of the FRESHER project.

Step 2: identification of central actors

In a second step central actors within the network are identified. As already mentioned the network consists of Twitter users sending messages with the hashtag *#ncds* or being mentioned in such a message. Table 2 shows the top ten users in the network with highest number of followers. The list is clearly dominated by leading news websites and news agencies such as The New York Times (1), Reuters (3), Forbes (4), Mashable (5) and Washington Post (6). Other user profiles in

Table 1 Top ten web-links in the network of *#ncds*, source: Author's data

No.	Website header	Type of source	Count
1	Updates from the Field...Protecting Health and Building Capacity Globally Division of Global Health Protection Global Health CDC	governmental organization report	47
2	dghp-field-updates-2015-summer.pdf	governmental organization report	42
3	Tax on sweet drinks Barbados Today	news article	36
4	Store - Exercise Works!	commercial website	30
5	Tax sugary drinks by 20%, say doctors - BBC News	news article	29
6	BMA - Food for thought British Medical Association	governmental organization report	29
7	PLOS Medicine_ Noncommunicable Diseases_ A Globalization of Disparity?	science journal article	28
8	The New Frontier of Non-Communicable Diseases Clinton Foundation	NGO/private initiative report	25
9	Sustainable development needs sustainable financing — tackling NCDs is no exception Devex	NGO/private initiative report	23
10	Innovation Countdown 2030 Identifying the most promising global health innovations	NGO/private initiative report	23

Table 2 Top ten users with the highest number of followers in the network of #ncds (“HQ” stands for “headquarter”), source: Author’s data

No.	User name	Real name	Nationality	Followers
1	@nytimes	The New York Times	US	18,974,524
2	@narendramodi	Narendra Modi	IN	14,781,807
3	@reuters	Reuters Top News	Int. (HQ: UK)	8,379,329
4	@forbes	Forbes	Int. (HQ: US)	6,566,664
5	@mashable	Mashable	Int. (HQ: UK, US)	5,604,947
6	@washingtonpost	Washington Post	US	4,725,133
7	@un	United Nations	Int. (HQ: US)	4,682,176
8	@unicef	UNICEF	Int. (HQ: US)	4,539,643
9	@potus	Barack Obama	US	3,870,634
10	@wef	World Economic Forum	Int. (HQ: CH)	2,636,423

the list belong to the Prime Minister of India Narendra Modi (2), the President of the United States Barack Obama (9), the United Nations (7), United Nations International Children’s Emergency Fund (8), and the World Economic Forum (10). The list also shows that three of these user profiles are located in the United States, while four of them represent international organizations or media companies with headquarters in the USA. The remaining three belong to Narendra Modi in India, Reuters with headquarter in UK and the World Economic Forum with headquarter in Switzerland.

All followers of a user receive his or her tweets on their Twitter wall. If for example @nytimes tweets (or retweets) a message including the hashtag #ncds nearly 19 million users are potentially reading that message. Therefore the number of followers can be seen as a way to measure the level of attention a user gets on Twitter. However, measuring the level of attention in this way leaves an important question open: Do the followers of this user really *read* this message or does it get lost in the vast information flow one user is confronted with when following a large number of accounts? Therefore the number of followers of a user must be regarded as a rather indirect or hypothetical level of attention.

Another way to measure the attention users receive on Twitter is to count their in-degree number within the network. The in-degree is defined by all edges in a directed graph going to a vertex (user), which can be tweets (in the form of one self-loop, no matter how many messages a user sends), mentions (mostly in the form of retweets) or replies to another user. Being mentioned in a tweet, being retweeted, or getting a reply requires active involvement of another user. If, for example, a message from @ncdalliance is being retweeted from several other users, it can be assumed that all these users have read this message and regarded it as worth to be spread. Thus, while the number of followers can be seen as a measure of *indirect attention*, the in-degree number can be seen as a measure for *direct attention* supported by action.

Table 3 shows the ten users with the highest in-degree number in the network. Top on the list is the account of NCD Alliance, a network of over 2.000 non-governmental organizations, followed by the account of the NCD Asia Pacific Alliance with headquarters in Japan, and the account of the World Health Organization on number 3. The other user accounts belong to NCDFREE, an international network of young professionals against NCDs, the British charity C3

Table 3 Top ten users with the highest in-degree in the network of #ncds (“HQ” stands for “headquarter”), source: Author’s data

No.	User name	Real name	Nationality	In-degree
1	@ncdalliance	NCD Alliance	Int. (no official HQ)	173
2	@ncd_apa	NCD Asia Pacific Alliance	Int. (HQ: JP)	136
3	@who	World Health Organization	Int. (HQ: CH)	128
4	@ncdfree	NCDFREE	Int. (no official HQ)	110
5	@c3health	C3 Collaborating for Health	UK	88
6	@dougundp	Douglas Webb	US	84
7	@cdcglobal	Centers for Disease Control and Prevention	US	82
8	@anantbhan	Anant Bhan	IN	65
9	@prevention1stau	Prevention 1st Australia	AU	54
10	@fcafortc	Framework Convention Alliance	Int. (HQ: CH)	45

Collaborating for Health, Douglas Webb (who is a health and development expert at United Nations Development Programme), CDC Centers for Disease Control and Prevention (the American health protection agency), Anant Bhan, Professor for bioethics and global health at Yenepoya University in Pune, India, Prevention 1st (a campaign by the Foundation for Alcohol Research and Education and the Public Health Association of Australia), and the Framework Convention Alliance for Tobacco Control. Regarding the origin of the user profiles the list shows that five of them belong to international organizations, two profiles belong to users in the United States, and one belongs to the UK, India and Australia each.

Figure 2 shows a graph including all vertices in the network. The size of the vertices is proportional to the number of followers; the top ten users with the highest number of followers have name labels. By contrast, Fig. 3 shows the same graph including the network edges. Here the vertices with the highest in-degree number (user from Fig. 5) are presented in dark blue and have name labels. For a better overview all self-loop-edges are excluded. It is clear to see that all of the highlighted vertices in the second graph show a high number of edges.

Comparing both approaches, highlights that the second approach is more favorable in order to identify important actors in the network. While most of the user accounts with the

highest number of followers come from mass media news sites or some of the world's leading international organizations, user profiles with the highest in-degree number mainly come from non-governmental organizations, governmental agencies or activist groups that specialize in the field of NCDs. With regard to RQ2 it can be stated that it is to a certain extent useful to consider some of the central actors as experts for interviews or as general contacts for the FRESHER project. Since the FRESHER workshops focus on participants from continental Europe, the aptitude of these users as participants for the workshops is rather limited.

Step 3: hashtag analysis

In a third and final step of the study a closer look is taken at the hashtags included in the Twitter messages of the dataset. Besides the key hashtag *#ncds* the dataset contains 713 other different hashtags. 1,391 edges contain only *#ncds* while the remaining 3,698 edges also contain one or more other hashtags. Table 4 shows the top ten hashtags in the dataset. Most frequent beside *#ncds* are *#diabetes*, *#publichealth*, *#globalhealth*, *#ffd3*, *#obesity*, *#sdgs*, *#health*, *#tobacco*, and *#cancer*. While the meaning of most of these terms is obvious, two of the hashtags are abbreviations (number 5 and 7) standing for the Third International Conference on Financing for Development

Fig. 2 Network actors highlighted by number of followers. (Graph showing all vertices in the network of *#ncds*. Size and opacity of the vertices is proportional to the number of followers on Twitter. Top ten users with highest number of followers have name labels.) Source: Author's data

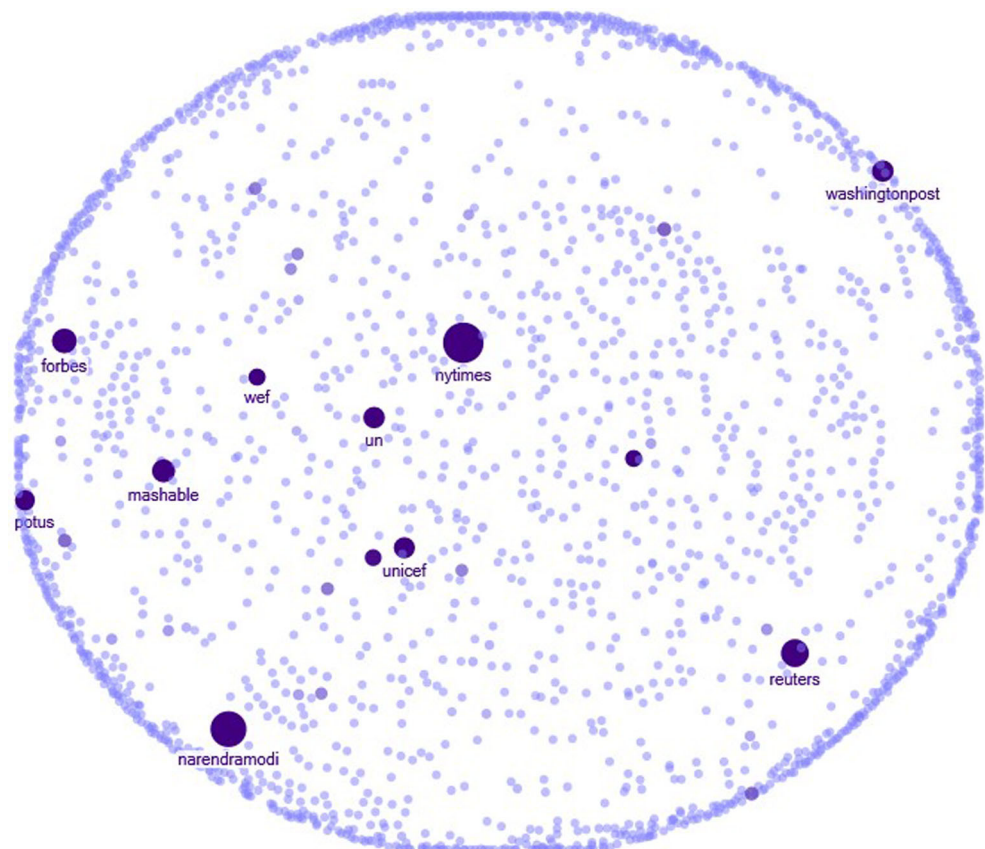
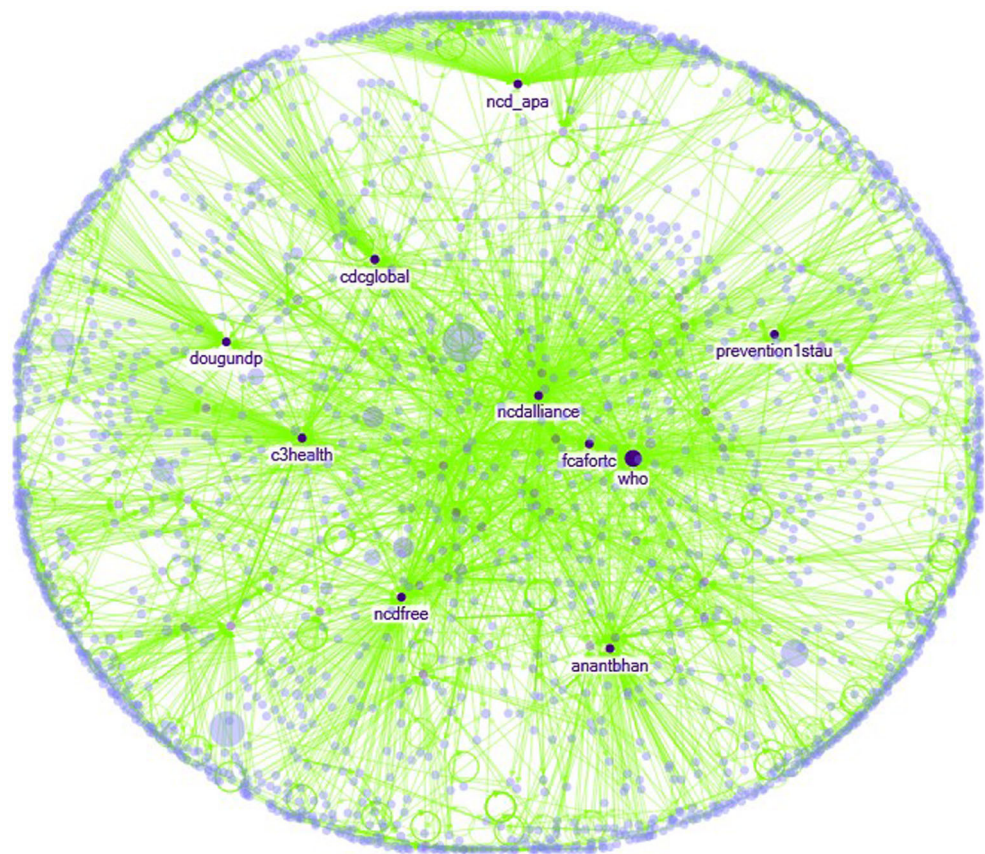


Fig. 3 Network actors highlighted by in-degree number. (Graph showing all vertices and edges in the network of #ncds. Size of the vertices is proportional to the number of followers on Twitter. Top ten users with highest in-degree number have name labels.) Source: Author's data



(#ffd3), which was held from 13th until 16th of July in Addis Ababa, Ethiopia, and the Sustainable Development Goals 2030 (#sdgs), formulated by the United Nations in 2015 to replace the Millennium Goals from the year 2000.

The word cloud in Fig. 4 displays all hashtags appearing 15 times or more in the tweets of the dataset. The key hashtag #ncds was excluded for a better overview. Color and size vary in proportion to the frequency of the hashtag terms, from bigger and dark blue for the most frequent hashtags to smaller and light blue to the less frequent ones. The highest occurring

hashtags from table 4 can be clearly identified in the word cloud. Other frequently appearing hashtags are for example #india, #sugar, #prevention, #physicalactivity, or #mentalhealth. Most frequently mentioned types of NCDs in the form hashtags are diabetes, obesity, and cancer. The word cloud illustrates very well the dominating topics in the Twitter debate on NCDs during the observed time period.

Table 5 shows different types/groups of NCDs plus corresponding determinants and drivers that have been identified previously in the FRESHER project on the basis of the bibliometric analysis and expert feedback. All terms showing an exact correspondence to hashtags in the dataset are marked green. All terms containing parts of hashtag terms or having a clear relation to some of the hashtags without showing an exact correspondence (e.g. “access to medication” and #accessmedicines, “lack of physical activity” and #physicalactivity, or “wellness movement” and #wellbeing) are marked yellow. Nine NCDs show exact correspondence with hashtags, as well as nine terms defined as determinants and six terms defined as drivers of NCDs. With regard to RQ3 it can be said that tweets with the hashtag #ncds contain other hashtags representing some of the determinants and drivers of NCDs although by no means all of the defined determinants and drivers are included in the list of hashtags.

Table 4 Top ten hashtags in the dataset, source: Author's data

No.	Hashtag	Count
1	#ncds	3656
2	#diabetes	219
3	#publichealth	177
4	#globalhealth	167
5	#ffd3	152
6	#obesity	151
7	#sdgs	147
8	#health	131
9	#tobacco	123
10	#cancer	110

Table 5 Types/groups of NCDs, determinants and drivers

NCDs	Determinants	Drivers
<i>Cardiovascular disease</i>	<i>Alcohol; tobacco; lack of physical activity; gender; drug consumption; nutrition; genetic inheritance; hypertension</i>	<i>Educational background; personalized health; safe environment; nutrition (vegan & vegetarian consumption); green city planning; social innovations (food, nutrition, care; physical activity); subsidize fresh fruit & vegetables; transplantation of organs; wellness movement; active gaming; nutrition (salt, fat, sugar); access to medication; land use/urban form; Mediterranean diet; advertising/commercials; prevention; screening</i>
<i>Cancer</i>	<i>Emissions; noise; industry; bad waste of chemicals and radioactivity; alcohol; aging; sun exposure; meat consumption; tobacco; no vegetables; lack of vitamins; chemicals and toxic agents; genetic inheritance</i>	<i>subsidize fresh fruit & vegetables; gluten epidemic; food labeling, organic farming; industrialization of food production; agriculture; access to vaccination (HBV, HPV); demographic change; monopoly/oligopolies of pharmacy; food</i>
<i>Depression</i>	<i>lack of physical activity; family mental health (genetics and social); unemployment; gender; social inheritance; doing things you like; childhood abuse; stress; no work-life balance; sun exposure</i>	<i>access to sports infrastructure; gender specific care; prevention; wellness movement; taxation of food, alcohol, tobacco; carbo-hydrate intense food; advertising/commercials; monoculture/standardization of food; nutrition (vegan & vegetarian consumption); food labeling; climate smart agriculture; organic farming; industrialization of food production; agriculture; standardization of food & food production; designer food; multinational corporations; fractionalization; financial status; education/new values for life; green city planning; social life/network; new social networks (IT); new media (tv, pv); lack of psychological resilience; company strategies for balanced work-life; educational background; division of labor; family status/single mums; changes family structures</i>
<i>Diabetes</i>	<i>nutrition (salt, fat, sugar)</i>	<i>subsidize fresh fruit & vegetables</i>
<i>Hypertension</i>	<i>environment: softeners</i>	<i>access to medication</i>
<i>Hypoglycemia</i>	<i>lack of physical activity</i>	<i>Mediterranean diet</i>
<i>Liver disease</i>	<i>alcohol; nutrition (salt, fat, sugar); drug consumption; medications</i>	<i>transplantation of organs; prevention/therapy; breeding/engineering human organs; nutrition (vegan & vegetarian consumption)</i>
<i>Metabolic syndrome</i>	<i>tobacco</i>	<i>green city planning</i>
<i>Musculoskeletal/osteoporosis</i>	<i>lack of physical activity; nutrition (salt, fat, sugar); gender (menopause); no work-life balance</i>	<i>land use/urban forms; gender specific care; genetics</i>
<i>Neurodegenerative disease (e.g. dementia)</i>	<i>low brain training; tobacco; lack of physical activity; alcohol; drug</i>	<i>brain training; mental health; level of education/schooling; active</i>

Table 5 (continued)

NCDs	Determinants	Drivers
	<i>consumption; advanced age; low education; chemicals and toxic agents</i>	communities; availability of fresh fruit & vegetables; cardio fitness
<i>Obesity</i>	genetic inheritance	personalized health/gene banks
<i>Respiratory disease (COPD, asthma etc.)</i>	<i>Emissions; noise; lack of physical activity; financial values; no work-life balance; tobacco; obesity; genetic inheritance; stress; drug consumption; child health/maternal health</i>	<i>Pollution; green city planning; climate change; social innovations (food, nutrition, care, physical activity); safe environment; monitoring; availability of information air quality</i>

(Terms showing an exact correspondence to hashtags in the dataset are written in italics and marked green. Terms containing parts of hashtags or having a clear relation to some of the hashtags without showing an exact correspondence are written in italics and marked yellow.) Source: Author's data

new traces, which is often helpful when working on future scenarios.

Another argument in favor of a Twitter data analysis to complement the scanning process of a Foresight exercise is the relatively short amount of time in which such an analysis can be done. While the analysis demands good preparation to meet the purpose of each specific Foresight (e.g. adjust the focus of the data analysis, defining the appropriate hashtags etc.), the analysis itself can be done within a couple of days, or, depending on the goals of the analysis, even hours, due to its semi-automated nature. This enables Foresight practitioners to get valuable insights into a public debate while keeping the additional input of resources on a small level.

A limitation of the study is the time frame of two months as a basis for data retrieval. All statements and assumptions regarding shared content, network actors, or hashtags only apply to the time from July 5th to September 7th. Longer time periods or another time frame might have led to different results. It is therefore obvious that this Twitter data analysis can complement but not substitute the bibliometric analysis of scientific articles, which in contrast examines a debate in a scientific community over a relatively long time period. Also, the limited time frame makes it impossible to make assumptions about topical trends emerging in the public Twitter debate. In order to talk about trends, or at least trending topics, it is essential to capture longitudinal data, making it possible to observe for example the rising frequency of specific hashtags or hashtag combinations over time.

It should also be noted that there are certain limitations associated with hashtag-based approaches, which have already been discussed in the literature. These critics usually emphasize the concern that a concentration on hashtags might exclude a good amount of other Twitter messages on the same topic. Bruns and Burgess [4] for example hint at the self-selecting mechanism of hashtags and believe that hashtag-based analyses “cover only the tip of a communicative iceberg” while other users respond to hashtagged tweets without including this hashtag in their replies. They also point out

that hashtag research crucially depends on the existence of a widely adopted hashtag term. Thus, there is always a remaining uncertainty that tracked data based on a selected hashtag missed out on alternatives contributing to the same discussion [5], a fact also Jungherr adds for consideration [25].

Both critics are justified to a certain extent. Concentrating on a specific hashtag to capture a public Twitter debate will probably always exclude some messages contributing to the same topic without using this hashtag. Still, the hashtag-based approach is an easy and effective way to capture at least a good part of the debate – and, what is even more important, to capture that part of the discussion which is consciously contributed by knowing and using a specific hashtag. Especially in the case of identifying central actors in the debate, this part is obviously the most interesting. Regarding the other critical point, the author tried to reduce the risk of potentially selecting the wrong hashtag or ignoring important alternatives by conducting a pre-analysis described in chapter 4.1.

The question, of whether Twitter data is representative of a population, was answered before and can be answered again with a simple “no”. This is the reason that previous attempts such as election prognosis were doomed to fail. Twitter users are likely to be a bit younger, higher educated, more political and societal interested, and more active in terms of communication. As already stated, a demographic shift from the average is not necessarily a problem as representative data is not essential in order to capture a public debate and to identify central actors within this debate. But the question for representative data leads to another one, which has to be discussed: Is Twitter data generally biased by PR professionals, spin-doctors or lobbyists?

In fact, this question is a bit more difficult to answer – and it is probably best answered with “yes” and “no”. Yes, communication on Twitter is shaped by different users sometimes on behalf of political actors, companies, or organizations trying to push forward their messages, products or opinions. Previous studies reported the potential misuse of Twitter for

spam and message attacks from political communities or companies by using automated scripts or other tactics [28, 32]. Must Twitter data therefore generally be seen as biased? No, the value of Twitter data depends largely on the research question to be answered. In this study it was tried to find out who dominates the debate surrounding NCDs on Twitter (in terms of receiving attention from other users), which subtopics are discussed and what kind of information is spread most frequently. This can be examined regardless of motivations driving the discussion.

Foresight practitioners must always be aware of (open or hidden) agendas potentially connected to information sources at different steps of a Foresight. The personal motivations of interview partners, participants of workshops – or information distributors on Twitter for that matter – should be questioned and taken into account, whether they are politicians, scientists, or representatives from corporations, non-profit organizations or civil society. Nevertheless, one of the main goals of any strategic Foresight is to broaden the perspectives on possible future developments by implementing different views, opinions and information sources into different phases of a Foresight exercise. In this regard Twitter can and must be seen as a valuable contribution to this process.

This does not mean that other methods like surveys, bibliometric analysis or interviews should be disregarded. Twitter data analysis should rather be seen as one component in the interaction of different methods in order to get a wider spectrum and to sharpen the view of the topic under debate. In this regard, the author shares the opinion of Lazer et al. [28] when they consider that “instead of focusing on a ‘big data revolution’, perhaps it is time we were focused on an ‘all data revolution’, where we recognize that the critical change in the world has been innovative analytics, using data from all traditional and new sources, and providing a deeper, clearer understanding of our world”.

Thus, research in the future might focus on the integration of Twitter data analysis into a systematic and expedient multi-method approach for Foresight exercises. Another goal could be the development of a comprehensive framework for the use of Twitter in foresight in general – not only as a basis for data analysis at the beginning of a Foresight exercise, but also as a tool for communication during the whole Foresight process, a point which could not be further considered in this study. Twitter provides the opportunity to receive real-time feedback on ideas, to involve potentially large number of participants in a scenario process, and to disseminate the results of a Foresight, building for example on a previous network analysis. A comprehensive framework would enable a systematic and interactive use of Twitter in the different phases of strategic Foresight.

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