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Communities of shared interests and cognitive bridges: the case of the anti-vaccination movement on Twitter

Francois van Schalkwyk[1] · **Jonathan Dudek**[2] · **Rodrigo Costas**[2,3]

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Abstract

This paper presents an analysis of the anti-vaccination movement's referencing of research articles on the topic of vaccination in the social media network Twitter. Drawing on the concept of bibliographic coupling, the paper demonstrates how Twitter users can be coupled based on articles mentioned on Twitter. The sample applied consists of 113 open access journal articles. The combination of *tweeter coupling* with the respective stance of Twitter accounts vis-à-vis vaccination makes possible the creation of a network graph of tweeters mentioning this corpus of articles. In addition to a common interest in the scientific literature, the findings show distinct communities of shared interests within the anti-vaccination movement, and demonstrate that tweeter coupling can be used to map these distinctive interests. The emergence of Twitter accounts serving as *cognitive bridges* within and between communities is noted and discussed with regard to their relative positions in the network. This paper's results extend the knowledge on the application of altmetric data to study the interests of non-scientific publics in science; more specifically, it adds to the understanding of the potentials of open science and science–society interactions arising from increased access by non-scientists to scientific publications.

Keywords Cognitive bridges · Altmetrics · Twitter · Networks · Anti-vaccination · Heterogeneous coupling

✉ Francois van Schalkwyk
fbvschalkwyk@sun.ac.za

Jonathan Dudek
j.dudek@cwts.leidenuniv.nl

Rodrigo Costas
rcostas@cwts.leidenuniv.nl

[1] South African Research Chair in Science Communication, Centre for Research on Evaluation, Science and Technology (CREST), Stellenbosch University, Private Bag X1 Matieland, Stellenbosch 7602, South Africa

[2] Centre for Science and Technology Studies (CWTS), Leiden University, Wassenaarseweg 62A, 2333 AL Leiden, The Netherlands

[3] DST-NRF Centre of Excellence in Scientometrics and Science, Technology and Innovation Policy (SciSTIP), Centre for Research on Evaluation, Science and Technology (CREST), Stellenbosch University, Private Bag X1 Matieland, Stellenbosch 7602, South Africa

Introduction

In 2019, the World Health Organization (WHO) listed 'vaccine hesitancy' (the reluctance or refusal to vaccinate despite the availability of vaccines) as one of the top ten global health threats (WHO 2019). This coincides with communication technologies having changed fundamentally the nature of society (Castells 2009; Williams 2018). We live in a time of real-time mass self-communication on a global scale. In the first quarter of 2019, micro-blogging social media platform Twitter averaged 330 million monthly active users (Statista 2019a), while 2.9 billion people were using at least one of Facebooks' core products (Facebook, WhatsApp, Instagram or Messenger) (Statista 2019b).

Networked digital communication provides opportunities to study communication in ways previously unimaginable. Included in the array of possible studies is the interaction between society and science—one of its most trusted institutions (Weingart and Guenther 2016). The study of science–society interaction is highly relevant since science communication impacts on human decision-making and behaviour, and consequently plays a critical role when society is confronted by serious health challenges.

The purpose of this study is to explore how science–society interactions can be studied using a combination of bibliometric, webometric and altmetric approaches, with a specific focus on the real-world applicability of altmetrics (Costas et al. 2016; Haustein et al. 2016; Robinson-Garcia et al. 2018). More specifically, because the heterogeneity of social media broadens the scope of science–society interactions "in a way that no other source does" (Robinson-Garcia et al. 2018: 825), the study explores the use of "heterogenous coupling" (Costas et al. 2017) and network analysis (Venturini 2012) to gain new insights into how society interacts with science.

The study chooses to focus on the anti-vaccination movement to illustrate the potential of such an approach to generating insights with application to real-world problems such as vaccine hesitancy. While this study is highly relevant, it is also largely exploratory, and the intention of this paper aligns with a progressive approximation approach (Venturini 2012) by sharing its novel methods and findings with the intent to stimulate further study that is equally relevant to society.

Conceptual framework

Advances in communication technologies have transformed the inter-connectedness of society to the extent that communication networks provide the primary setting for human agency (Castells 1996, 2009). The basic elements of the network society are not material, but become manifest in the intangible flows of information produced by and processed through communication networks: information to communicate among people, to control processes, to check and re-evaluate existing information, and to produce more and new information (Stalder 2006). Among these communication networks are social media platforms such as Facebook and Twitter.

As actors interact in social media spaces, connections emerge into complex social network structures (Monge and Contractor 2003) that reflect patterns of shared interest or cognitive coherence. From these network structures, clusters of proximal social actors emerge, and these may reflect shared aspirations, purpose or identities. These clusters may also represent 'communities of attention' (Haustein et al. 2015a, b; Díaz-Faes et al.

2019) or, more specifically, communities of shared interests in online communication networks.

Communities of attention in online communication networks may constitute social movements; collectives of social actors that act self-consciously to effect change (Stalder 2006). In a globally networked society, social movements are no longer bound by place and are more readily able to communicate in real time on a global scale to bring about social change (Castells 2015), although some scholars question the potential of social media communication networks to foment lasting social change (Gerbaudo 2012; Miller 2017).

The emergence of information and communication technologies has seen a range of impacts on science–society interactions. There has been a marked increase in accessibility of scientific journals (Archambault et al. 2014; Piwowar et al. 2017) as science becomes more open to society. There have also been increases in the presence of journal articles on social media platforms (Haustein and Costas 2015; Haustein et al. 2015; Thelwall et al. 2013). During the past few years, there have been several studies investigating mentions of scientific articles on Twitter (Didegah et al. 2018; Haustein et al. 2014, 2015; Mohammadi et al. 2018; Nelhans and Lorentzen 2016; Puschmann 2014; Tsou et al. 2015; Vainio and Holmberg 2017; Zhou and Na 2019) and, to a lesser degree, on Facebook (Enkhbayar et al. 2019; Mohammadi et al. 2019). These are mostly studies that rely on altmetric approaches—that is, they focus on the presence of scholarly outputs in the social media (Cronin et al. 1998; Priem et al. 2011).

Greater openness in science is seen as a necessary evolution in the efficiency, quality and contribution of science to society (Jasanoff 2006; Leonelli et al. 2015). In effect, open science has made possible increased public access to science, while new online communication technologies have provided the space for interactions between scientists and diverse publics, including social movements, as well as the means to trace social interaction (Venturini 2012). This development also raises concerns: How do ideologically motivated publics that self-organise into social movements and attentive to science, access and disseminate scientific information as part of their communication strategies?

Science journalists and the media have traditionally been the primary interface between science and the public (Weingart 2011, Schäfer 2017). There is, however, a simultaneous decline in science journalism (Guenther 2019; Schäfer 2017), an increase in the scramble for attention among a variety of stakeholders (Weingart and Guenther 2016; Williams 2018), and the emergence of social media as a new, informal, interpersonal channel of communication between scientists and the public (Southwell 2017), shaped by new logics of interaction (Van Dijck and Poell 2013). Bucchi (2018) describes a ‘crisis of mediators’ in which new scientific research is fed in real time into the public domain without being filtered by communication professionals. As scientific information becomes more accessible, attentive non-scientist publics are presented with a pluralistic universe of information providers and must choose whom to trust as authoritative sources of ‘scientific’ information (Blöbaum 2016; Weingart and Gunther 2016).

As a socially constructed space, the organisation of actors and their relationships in communication networks (Castells 2009; Venturini 2012) is key to understanding the delivery, reception, use and impact of science. We expect social movements to play a strategic role in the amplification of information extracted from openly accessible products of science in their communication networks (Van Schalkwyk 2019b). Individual actors may mediate in new ways (Landrum 2017; Scheufele 2014) between science and a social movement such as the anti-vaccination movement. Hence, this paper seeks to establish whether the anti-vaccination movement is present in a network predicated on the sharing of scientific information in the social media, and whether the composition of such a network may reveal different communities of interest within the communication network.

The case of the anti-vaccination movement

As far back as 2005, researchers were aware of the potential harm that could result from the use of science as a source of health information by ideologically motivated social movements (Zimmerman et al. 2005). Others (Bennato 2017; Bean 2011; DiResta and Lotan 2015; Kata 2012; Leask 2015) reinforce this concern, arguing that the effects of activist groups should not be underestimated. Through the social media in general, and Twitter in particular, anti-vaccination promotors yield considerable influence over the general public, particularly among those faced with decisions about whether to vaccinate their children.

Scientists warn that what may seem like negligible decreases in vaccination rates can have dire health outcomes as herd immunity is compromised (Lo and Hotez 2017). While national average vaccination rates have remained relatively stable, there are geographical enclaves where vaccination coverage for vaccine-preventable diseases has decreased (Bean 2011; CDC 2013; Kahan 2014; Vanderslott and Roser 2018). Since 2014, new cases of vaccine-preventable measles have been recorded in several countries where the disease was thought to have been eradicated (CDC 2015; Moten et al. 2018; WHO in BBC 2019). Of equal concern is the belief held by more than 20% of the general population in countries such as France, Russia, Japan, Italy, Greece, Iran and Vietnam that vaccines are harmful (Larson, et al. 2016). Furthermore, vaccine refusal has been found to occur in geographically dispersed social clusters (CDC 2013). This suggests that increased levels of information sharing across distances made possible by information and communication technologies can contribute to dispersed outbreaks attributable to vaccine refusal. While constraints in the supply of vaccinations also inhibit increases in vaccine coverage (Vanderslott & Roser 2018), given the evidence available, the role of communication in shaping perceptions and amplifying anti-vaccination messaging cannot be ignored (Van Schalkwyk 2019b), particularly if 'philosophical objections' rather than supply constraints accounted for 79% of measles vaccination refusals in 2012 in the US (CDC 2013).

Several studies have explored the use of the web and social media by the anti-vaccination movement. These studies focus predominantly on strategies and tactics rather than on the use of scholarly publications by the anti-vaccination movement (Bean, 2011; Bennato, 2017; Cuesta-Cambra et al. 2019; Kata, 2012; Mitra et al. 2016; Moran et al. 2016; Sanawi et al. 2017; Yuan et al. 2019). As indicated above, there have also been several recent studies investigating mentions of scientific articles in conversations in the social media, but these studies do not focus explicitly on the anti-vaccination movement. In other words, while there have been many studies on science in the social media, and studies on the social media communication strategies of the anti-vaccination movement, to the best of our knowledge, there are no studies that focus on mentions by the anti-vaccination movement to open access journal articles in the social media. For open science to be both judiciously deployed and purposeful, a deeper understanding of the use of open science by non-scientific publics is therefore relevant.

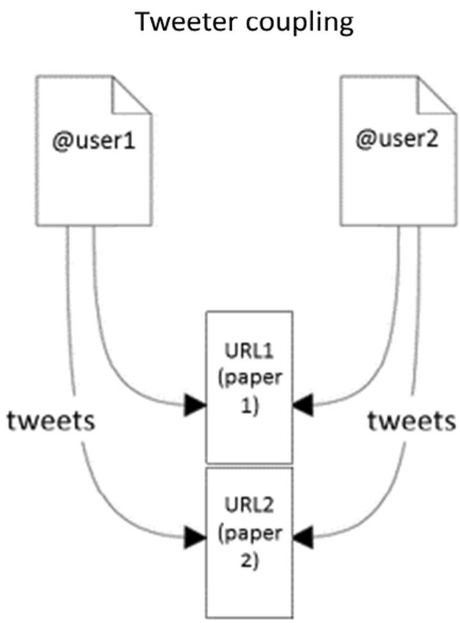

Fig. 1 Coupling of tweeters over shared publications (Costas et al., 2017)

Methodology

By means of a case study, the research presented here is centred around social media activities of the anti-vaccination movement, more specifically the interactions on Twitter by those who are opposed to vaccinations with open access journal articles on the topic of vaccination and autism. This selection allows for the observation of a non-scientific community with an explicit interest in and interactions with scientific findings.

All communication under study is focused on open access journal articles. This decision follows the thematic prerequisite of investigating the potentials of open science in the network society. For this study, a set of 113 open access journal articles on the topic of vaccination and autism was used (Van Schalkwyk 2018); this set was extracted from a previous study by Van Schalkwyk (2019a) on the potentials of open science.

To reconstruct networks from mentions of publications in the social media, all Twitter accounts that mentioned any of the 113 articles were identified as well as the number of tweets per Twitter account using data provided by Altmetric.com. This returned a total of 12,207 unique Twitter accounts and a total of 21,490 tweets, with the first tweet being posted on 3 July 2011 and the last tweet posted on 3 October 2017. Of the 113 articles, 103 were tweeted at least once and 86 articles were tweeted by more than one tweeter.

A network graph was created using the software package NodeXL Pro version 1.0.1.396 (Hansen et al. 2010) using data for both Twitter accounts and tweets mentioning an open access journal article in the set of 113 articles. To create this network, the approach of bibliographic coupling (Kessler 1963; Zhao and Strotmann 2008) was adapted for the social media and its affordances. Open access journal articles (linked objects) were used as a reference to create instances where two tweeters (users) tweet a link (URL) to the same open access journal article. Each pair of tweeters linking to a journal article in this manner is a couple, hence the network is described as a 'tweeter coupling network' (Costas et al. 2017). Figure 1 illustrates this concept.

Table 1 Number of papers co-mentioned on Twitter

No. of papers	No. of co-mentions (tweeter couples)
1	11,839,790
2	154,873
3	19,891
4	3728
5	698
6	279
7	113
8	69
9	17
10	10
11	6
12	5
13	1

Coupling indicates a type of connection based on a cognitive link or bridge between two tweeters. A *cognitive bridge* in this context is a connection that exists between two actors who share a common interest in an idea or set of ideas. It is not necessarily the case that there is cognitive alignment or harmony between bridged actors; rather, what bridges them is their shared interest in an idea. Cognitive coupling in the social media is distinct from, for example, social or semantic coupling which are premised on other links such as followers or hashtags respectively.

In the manner described above, a matrix of coupled tweeters was created based on the Twitter accounts that co-mentioned one of the journal articles in the sample. Of the 103 articles tweeted, 86 articles were tweeted by more than one tweeter and could thus be considered. Table 1 shows the number of co-mentions per number of co-mentioned publications. In total, this returned 12,019,480 co-mentions of articles. Of those, by far the largest share of co-mentions is based on only one article. On the other hand, the largest number of distinct articles mutually shared by two tweeters is 13.

In order to be considered in the subsequent network analysis, two tweeters needed to be coupled by at least three articles. This limit was imposed based on the recommendations of the developers of the software used to create the network graph (Smith 2018) but also to reduce the complexity of the social map for the purposes of analysis (Venturini 2012). NodeXL Pro was used to further process the tweeter pairs and co-occurrences data, to manually capture the overlay data for vaccination stance (from Van Schalkwyk 2019a[1]),

[1] Using a web crawler to identify anti-vaccination accounts followed by manual verification of the Twitter accounts, Van Schalkwyk (2019a) identified 658 anti-vaccination accounts that mention open access journal articles on the topic of vaccination and autism. From the manual verification process, several pro-science accounts were also identified. Anti-vaccination Twitter accounts were defined as those that regularly tweet or retweet content to persuade others of the dangers of vaccines, while pro-science accounts were those that (re)tweet to defend the consensus position of science, that is, that vaccines are effective in combatting infectious diseases and pose no material health risks to those who are vaccinated. The data on stance, while not comprehensive in the sense that it provided classifications for all tweeters in the tweeter coupling network, was added to NodeXL to provide additional information in the analysis of the network.

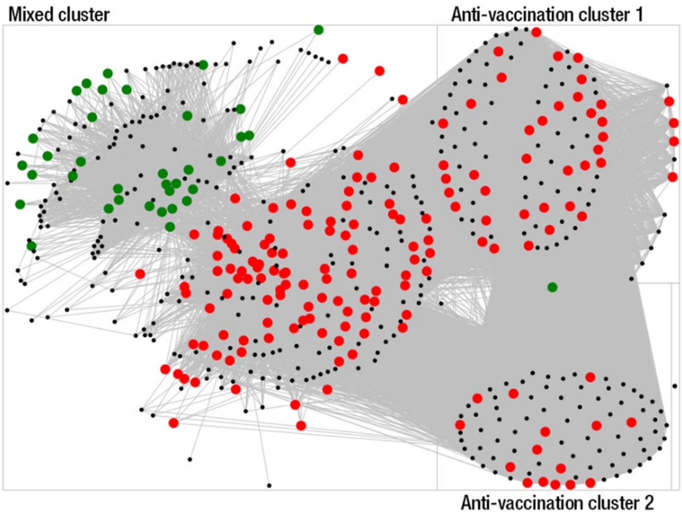

Fig. 2 Tweeter coupling network (N = 12 207)

and to calculate the network metrics. The network graph (Fig. 3) was generated in NodeXL Pro using the Harel-Koren algorithm (Harel and Kohen 2001). Both available algorithms in NodeXL Pro—the Harel-Koren and the Fruchterman-Reingold algorithms—were tested and found to generate similar graphs in terms of clustering. The Harel-Koren-generated network graph was preferred for its clarity in terms of how the clusters were positioned in the graph, particularly the rendering of what was identified as the mixed cluster in the graph.

Findings

Figure 2 shows a tweeter coupling network in which each pair of Twitter accounts shares a mention to 3 or more of the 103 open access journal articles related to the topic of vaccination and autism. The colour of each node shows the stance of the tweeter vis-à-vis vaccination as determined by Van Schalkwyk (2019a). Red nodes show *anti-vaccination* accounts while green nodes show *pro-science* Twitter accounts; the stance of the black nodes is unknown.

The tweeter coupling network in Fig. 2 reveals several noteworthy characteristics. The first is that it is possible to generate a tweeter coupling network graph using altmetric data that includes mentions of journal articles with topical similarity. This confirms previous research that the formal communications of science are being mentioned on the social media platform Twitter but adds new information about the relationships between tweeters. The second noteworthy characteristic of the graph is the clustering of Twitter accounts into three distinct groups based on their relationships (i.e. the extent to which they mention the same journal articles in the sample). The two groups on the right-hand side of the graph are composed of anti-vaccination accounts. The third ‘mixed group’ (on the left-hand side of the graph) consists of both pro-science and anti-vaccination accounts, although there is a discernible separation within this group according

Table 2 Top 10 accounts by degree centrality score in the tweeter coupling network

Account	Stance	Degree centrality
@itsmepanda1	Anti-vaccination	404
@LaLaRueFrench75	Anti-vaccination	365
@debnantz	Anti-vaccination	344
@eTweeetz	Anti-vaccination	340
@Biegenzahn	Anti-vaccination	335
@libertylives277	Anti-vaccination	319
@EMcCra2	Unknown	318
@aspiritcan	Anti-vaccination	309
@SNCCLA	Anti-vaccination	304
@VaxChoiceVT	Anti-vaccination	303

to stance: pro-science accounts are clustered in the top left, while anti-vaccination accounts are clustered in the bottom right and closer to the two anti-vaccination groups.

Algorithms for calculating centrality extend the analysis beyond communities of shared interests to the positions of individual tweeters relative to others in the same network. This provides insight into who the most active coupled tweeters are in the sense that they display topical dominance in a network predicated on journal articles dealing with the topic of vaccination and autism.

Table 2 shows those network nodes with the highest *degree centrality* scores, i.e. those nodes with the greatest number of shared mentions with other nodes in the network. We interpret degree centrality in this network graph as being indicative of both level of activity *and* the extent to which a tweeter mentions the same articles as others in the network. In other words, while those accounts with high degree centrality scores are the most active to the extent that they mention journal articles more frequently than others in the network, they are also those tweeters who have the most mentions of articles in common with other tweeters. Being only a highly active tweeter is insufficient to obtain centrality in the network because a high level of activity does not necessarily imply shared mentions of articles.

Table 2 shows that all tweeters with the highest degree centrality scores are anti-vaccination. The account with the highest degree centrality is @itsmepanda1 (404). The pro-science Twitter account with the highest degree centrality score is @dkegel (140), followed by @doritmi (135).

Betweenness centrality indicates how important each node is in providing a bridge between different parts of the network. This bridge represents the extent to which a node is part of 'transactions' among other nodes and is therefore an important indicator of which nodes facilitate the flow of information between other nodes in the network. In the case of the tweeter coupling graph, there is no active interaction or transmission of information between tweeters. The betweenness centrality of nodes in the graph cannot therefore be interpreted in terms of active bridging. We interpret the betweenness centrality in the tweeter coupling graph as indicating those tweeters who emerge more prominently in network positions that are between different communities. While some anti-vaccination nodes have both high degree centrality and betweenness centrality scores (@itsmepanda1, @eTweetz and @LaLaRueFrench75), new pro-science nodes

Table 3 Top 10 accounts by betweenness centrality in the tweeter coupling network

Account	Stance	Betweenness centrality
@itsmepanda1	Anti-vaccination	18,087.753
@eTweeetz	Anti-vaccination	10,467.082
@dkegel	Pro-science	8694.468
@doritmi	Pro-science	7540.706
@PaulWhiteleyPhD	Unknown	7082.546
@Anwar_Hashem	Pro-science	6530.001
@Biegenzahn	Anti-vaccination	6398.226
@LaLaRueFrench75	Anti-vaccination	5834.115
@mission2heal	Anti-vaccination	4889.009

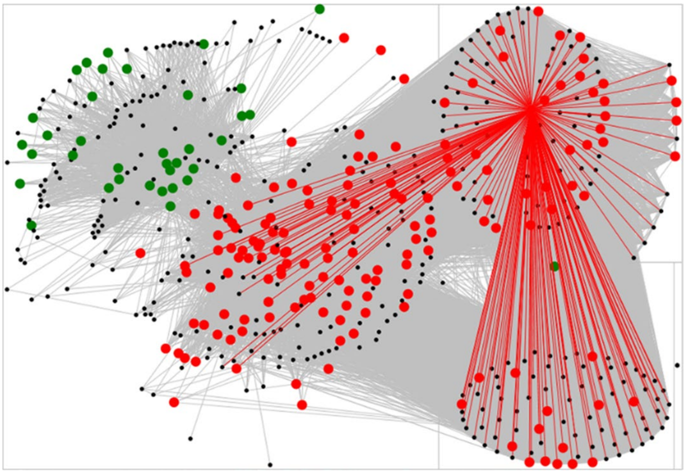

Fig. 3 Relative position of the highly active tweeter @LotusOak

(tweeters) emerge in the top accounts by betweenness centrality (@dkegel, @doritmi and @Anwar_Hashem).

Table 3 shows the 10 tweeters with the highest betweenness centrality. Given the structure of the network, it is not surprising to find pro-science accounts in the top 10 as one would expect there to be pro-science accounts that bridge between their own sub-group and the anti-vaccination sub-clusters in the mixed group.

Figures 3 and 4 show two patterns of shared mentions in the anti-vaccination movement by focusing on two tweeters, one with the highest degree centrality as apparent from Table 2 (Fig. 4) and one known to be a highly active anti-vaccination tweeter of mentions to journal articles (Van Schalkwyk 2019a; Fig. 3). The data shows that the highly active tweeter shared mentions to 5 articles while the highly central tweeters shared mentions to 13 articles in the sample. Figure 3 shows that the highly active anti-vaccination tweeter only spans the anti-vaccination clusters while Fig. 4 shows how the anti-vaccination Twitter account with the highest degree of centrality in the network spans the anti-vaccination clusters in the network, and also spans from the anti-vaccination accounts to the pro-science cluster in the network.

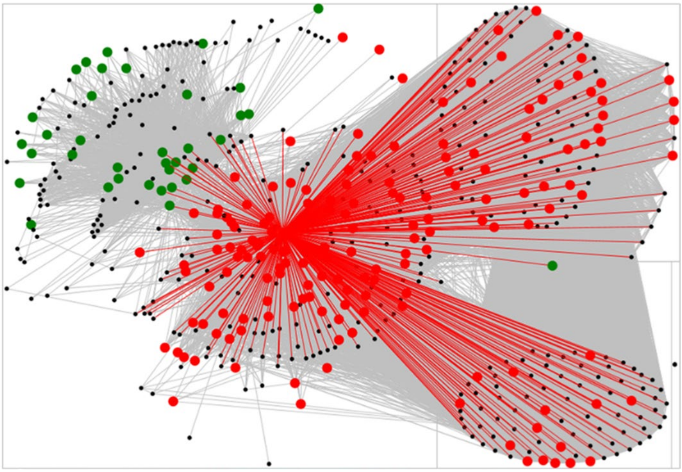

Fig. 4 Relative position of the highly central tweeter @itsmepanda1

Discussion

The findings from a network analysis of co-mentions to topically similar open access journal articles on Twitter indicate that rather than there being a single community, there are distinct sub-groups or communities of shared interests in the network. At the same time, there are actors—cognitive bridges—in the network that emerge in positions located between communities of shared interests.

Communities of shared interests

The exclusively anti-vaccination clusters or communities of shared interests (as illustrated in Figs. 3, 4) are present as sub-networks in a typical hub-and-spoke arrangement (Himelboim et al. 2017). These communities are centred around one or two Twitter accounts. However, unlike hub-and-spoke networks, the density of connections between the three anti-vaccination clusters appears to be relatively high, and this is attributable to high levels of cognitive coherence within each community.

The mixed group consisting of both anti-vaccination and pro-science accounts is consistent with previous research on communication patterns on Twitter centred around vaccination (Yuan et al. 2019), and shows a different type of network structure from the anti-vaccination communities; one that can be described as polarised (Himelboim et al. 2017). In this part of the network, links between the pro-science and the nearest anti-vaccination cluster are less dense while in-cluster density remains high. Polarisation might be a consequence of selective mentioning of specific journal articles, leaving little room for more nuanced positions or constructive engagement (Tucker et al. 2018; Yeo et al. 2015).

Barberá (2015) challenges the widely held view that social media intensifies polarisation by positing that social media usage reduces political polarisation because it increases incidental exposure to novel information. Consequently, the use of social media leads to an increase in exposure to a wider range of political opinions than those normally encountered offline. The findings of this research show evidence of polarisation and augmentation. The network analysis shows that there are closer conceptual ties within the anti-vaccination clusters by virtue of their more frequent and possibly highly selective interaction with scientific information extracted from open access journal articles (Van Schalkwyk 2019b). However, there is also evidence of tweeter coupling spanning across communities who hold different views on the topic of vaccination. This could suggest potential exposure to novel information as suggested by Barberá (2015) as well as more complex patterns of interaction with scientific information by social movements (Dubois and Blank 2018).

The attribution of stance to Twitter accounts by Van Schalkwyk (2019a) was not fine-grained enough to reveal salient characteristics that could be used to categorise sub-groups within the anti-vaccination movement. It is, however, likely that the different clusters or communities of shared interests evident in the tweeter coupling network can be attributed to the underlying reason for each cluster's resistance to vaccination. Based on content analysis of anti-vaccination tweets (Van Schalkwyk 2019a), at least three sub-groups can be described and may account for the two exclusively anti-vaccination clusters in the tweeter coupling network. A sub-group that advocates for moderation is against the use of multi-dose vaccines (such as the MMR vaccine), against the use of specific vaccines (such as the HPV vaccine) or against the number of vaccinations administered in early childhood. A homeopathic and natural healing sub-group is opposed to the use of specific non-natural and/or toxic ingredients or adjuvants such as aluminium in vaccines. A pro-choice sub-group is opposed to the limitations placed on the rights of parents to choose whether or when to vaccinate their children.

There is therefore a different *focus of attention* for each sub-group or community of shared interests, resulting in each community selecting and mentioning different journal articles on Twitter; articles that are most closely aligned to their motivations behind advocating for an end to vaccinations. At the same time, shared mentions *between* communities of shared interests are also evident, suggesting that while there may be variation in the focus of attention, there is nevertheless an overarching common interest in the advocacy efforts of the anti-vaccination sub-groups.

Cognitive bridges

The findings show that some actors are more active than others (i.e. they mention more articles than others) while also spanning several communities of shared interests by virtue of their topically broader collections of scientific articles. The concept of cognitive bridges as proposed in this paper provides a useful starting point for thinking about the possible roles that these actors play in communication networks, as well as the practical value of knowing who these bridging actors are.

Figure 3 shows that a highly active anti-vaccination tweeter only spans the three anti-vaccination clusters suggesting that this tweeter is limited to cognitive bridging *within* the anti-vaccination movement. Figure 4 shows how the anti-vaccination tweeter with the highest degree centrality and betweenness centrality in the network spans all three anti-vaccination clusters in the network, and also spans from the anti-vaccination accounts to pro-science cluster in the network, suggesting that this account represents a cognitive bridge between sub-networks within an aligned group, as well as between non-aligned sub-networks. In other words, the *highly active* tweeter mentions articles from a smaller set of possibly more similar articles, while the *highly central* tweeter mentions more articles from a more diverse set of articles in terms of the articles' findings regarding a relationship between vaccination and autism.

It may be tempting to describe the highly active and centrally located actors in the tweeter coupling network as intermediaries in a communication network. But to do so would imply a certain degree of active interaction between actors and of intervention on the part of those actors (Frandsen and Johansen 2015). The only interaction in the tweeter coupling network is between the actors and the open access journal articles when the actors extract information from the articles and insert that information into their tweets. In other words, the network graph and statistics show communities of shared interests and active disseminators in those communities, but do not represent direct interaction between tweeters.

Nevertheless, it is conceivable that while the tweeter coupling network may not represent actual interaction among tweeters, the identification of certain types of actors may provide a useful *starting point* for isolating intermediaries in communication networks. This may present an opportunity to restore a polluted science communication environment (Kahan 2013) or to disrupt nodes who contribute to its pollution. To illustrate, the identification of the cognitive bridge spanning opposing clusters in the network (Fig. 4) offers the opportunity to verify the extent to which this tweeter actually intermediates in the online communications between anti-vaccination tweeters and pro-scientists, and whether the tweeter could play a constructive role in online discussion and information sharing. The identification of a cognitive bridge between sub-clusters within the same social movement could point to intermediation of the kind that hardens beliefs across the movement and amplifies uncertainty in the broader communication network (Zannettou et al. 2017).

Attention and influence in communication networks

If influence is a new form of power in the network society (Muller 2017), then it becomes important to understand better not only who the possible intermediaries might be but also how they establish and protect their positions of influence over others in the network.

The concept of communities of shared interests used in this paper denotes a group of actors that emerges by virtue of an intersection of similarity between group members (e.g. similar aspirations, purpose or identity) resulting in a shared 'focus of attention' in its communication. The anti-vaccination movement's focal point is to oppose vaccination. The focus of attention is what *holds* the community's attention in the online communication network. At the same time, all actors in the network *seek* attention as they compete in a saturated communication environment to have their messages 'heard' by others in the network. To this end, they devise new communication strategies for attracting attention (Wu 2016; Williams 2018). Being active but disconnected limits amplification, as does being connected and invisible.

Attention-seeking strategies in networks are typically shaped by the logic or program of a network (Van Dijk and Poell 2013; Williams 2018). While there are multiple global communication networks, the contours of which are not always sharply defined, a network is defined by the program that assigns the network its goals and its rules of performance; in other words, the core logic of the network (Castells 2009). For example, scientists in the global science network seek attention in order to make other scientists aware of their truth claims; this is a critical component in the process of validating or certifying those claims (Roosendaal and Geurts 1997). However, across social media networks, there is no apparent central, unifying network program or logic to define or steer communication (Van Dijk and Poell 2013), and attention itself becomes the primary programmatic criterion for determining success in the network (Williams 2018). Under these circumstances, success in social media communication networks can be as banal as the number of followers or number of likes, but, in principle, can be any metric indicative of the attention attracted by a node in the network relative to the other nodes in the same network.

Prior research has shown how the anti-vaccination movement is able to attract disproportionate levels of attention in online communication networks to exert its influence over what is certain or true (Van Schalkwyk 2019b). The movement does so in an online communication network that does not function according to the same logic as science and this creates opportunities for strategic exploitation of the dominant *attention logic* of the communication network to destabilise what is known to be true; in effect, to amplify uncertainty. In this paper, we have shown how tweeter coupling can be used to create a relational network and to identify both communities and actors in social networks with a view to exploring further the roles they play in accessing and disseminating scientific information as part of their communication strategies.

Limitations and further research

Using the web as a site of study poses challenges (Haustein 2016; Rogers 2015). It is not uncommon for the corporate owners of data sources on the web to change the rules on how their data can be accessed and re-used. This may affect not only a researcher's ability to access data directly but may also compromise the functionality and usefulness of applications used to collect and analyse online data. There are also challenges with the stability of the data from online sources—websites disappear from the web for a variety of reasons, and users of social media close their accounts or change their account profiles (affecting either the content of those accounts or the accessibility of the account's content), and they usually also exhibit mechanistic and repetitive types of behaviour in their interactions with publications (Robinson-Garcia et al. 2017). These fluid conditions place challenges on the replicability of altmetric studies and on the verifiability of selected data referenced in the research (Haustein, 2016).

A further issue raised by Sugimoto et al. (2017) is the finding that discrepancies can exist when comparing results for mentions in the social media obtained from different aggregators. It is acknowledged that a limitation of this study is its dependency on data from Altmetric.com, and that the possibility exists that different results may be obtained when using any of the other available altmetric data sources [e.g. PlumX or Crossref—see also Zahedi and Costas (2018)]. Similarly, the findings could be made more robust by reducing the reliance on a single network graphing and analysis tool (i.e. NodeXL), and by introducing additional network analysis algorithms such as HITS or other random-walk based approaches to identify cognitive bridges and their relative positions in online communication networks.

Further research could provide more conclusive evidence on the selective mentioning of specific articles by different communities of shared interests. For example, the observation of the possible selective mentioning of journal articles, and of different articles being mentioned by different communities in the network graph, could be verified by classifying each of the articles in the sample according to the position of each *article* vis-à-vis vaccination, and assigning to the vertices in the graph an indicator to show the position of each article. One would expect pro-vaccine article vertices to be dominant in the mixed cluster, and the vertices of articles supporting the adverse effects of vaccination to be prominent in the anti-vaccination clusters. Such an approach would also reveal insights about the relationship between, on the one hand, the proportion of published studies in the sample that provides evidence for vaccination versus those against, and, on the other hand, the number of co-mentions for each article type in terms of the scientific evidence provided.

Research on nodes that emerge in-between communities of shared interests is needed to confirm their possible role as intermediaries, and, consequently, as important communicators in the network. A reconceptualization of the role of intermediaries in communication networks and how they may differ from traditional definitions of intermediaries may also be required because intermediaries in communication networks may intermediate in ways that are less active or intentional than is traditionally taken to be the case. Feng's (2016) notion of more passive 'information bridges' versus the more active 'influencers', 'network builders' and 'active engagers' may provide fertile ground for the conceptual development of intermediation in communication networks; as does research that shows that highly active provocateurs initiate conflict in online communication networks, but it is the less active who maintain the engagement between online communities in conflict (Kumar et al. 2018).

Conclusion

The use of scientific information to advocate for vaccine refusal is not trivial. The anti-vaccination movement is strategic in its use of social media to create and amplify uncertainty about vaccine safety in the broader public. Accessing information from scientific articles to bolster their claims forms part of the movement's communication strategy.

This paper has been shown that it is possible to create a tweeter coupling network using mentions on Twitter to open access scientific articles dealing with the contested topic of anti-vaccination. It has also shown that ideologically separated communities of shared interest exist in the network. The findings show different tweeters who command 'topical dominance' in the network while simultaneously spanning several communities by virtue of their topically broader collections of scientific articles. These tweeters are described as 'cognitive bridges' and may play important roles in the distribution of information in communication networks. Managing, controlling or amplifying information flows may depend on these important actors.

This paper has illustrated how Twitter mentions of scientific articles, the coupling of tweeters, and network analysis can be applied to developing a better understanding of science–society interaction in the social media. Additional empirical research on pathways, the attainment of centrality, intermediation, and the multiplicity of roles and characteristics of actors within online social movements is needed to further contribute to a more fine-grained empirical understanding of the potentials of open science and, more importantly, the question of how science can respond to the effects of greater openness and socially networked communication.

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Compliance with ethical standards

Conflict of interests The authors have no conflict of interests to declare.

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