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Abstract

Selective online exposure to information that serves to only affirm people's opinions or is strongly aligned with their interests is considered to be a major issue in modern societies. Echo chambers, for example, are online environments in which users are only exposed to confirming opinions and alternative voices are excluded or discredited. Echo chambers are considered to be particularly dangerous, because they may lead to polarization and even radicalization. Social media facilitate the formation of echo chambers as described in the Social Identity Theory by means of homophily and depersonalization. This can be especially harmful in the case of conspiracy beliefs, where particularly extreme opinions lead to a stronger seclusion from society, encourage socially destructive actions, and curate Fake News. In our research we will assess different echo chambers in terms of actively established common patterns of consumed online information sources. To that end, we analyse the news source Likes from over 7,000 users with their approximately 1,450,000 Likes on Facebook. We intend to identify different types of Facebook echo chambers with a focus on conspiracy groups, understand distinguishing characteristics in communicative behaviour of the conspiracy groups on Facebook and explore unique characteristics of users in conspiracy echo chambers.

Keywords: Facebook, Echo Chambers, Conspiracy Theories, Social Identity Theory, News, Media Consumption, Polarization

1 Introduction

In 2011 Eli Pariser, co-founder of the viral content site “Upworthy”, wrote a seminal book that pointed towards the danger of selective online information exposure (Pariser 2011). Five years later, following the US presidential election, respective effects in form of social media filter bubbles gained substantial public interest. They were in part associated with the unexpected persuasiveness of arguments to certain demographic groups and the inaccurate prediction of the election results (Baer 2016).

Echo chambers are environments in which users are exposed to conforming opinions, other voices are actively excluded or discredited, conflicting information may actually serve to reinforce the opinions (Nguyen 2018; Spohr 2017) to create enclaves of like-minded people that can lead to increased polarization (Dandekar et al. 2013). Particularly conspiracy sources publish unverifiable information with an extreme bias that is not always supported by evidence (Media Bias/Fact Check 2018a), which may threaten society and democracy when curating the belief in “fake news” (Sunstein 2018).

Online social networks have been found to play a strong role on this radicalization, for example, after 9/11 (Hamm and Spaaij 2015). The emergence of online echo chambers is theoretically grounded in homophily and depersonalization as outlined by social identity theory (Bakshy et al. 2015; Boutyline and Willer 2017; Dandekar et al. 2013; Jasny et al. 2015; Nikolov et al. 2015; Shalizi and Thomas 2011; Sunstein 2018). Homophily means the principle that similarity builds connections and structures network ties of every type (e.g., marriage, friendship, work, advice, support, information transfer) (McPherson et al. 2001). Depersonalization describes the process of deriving the own identity from the group norms instead of personal experiences (Carter 2015; Stets and Burke 2000).

Despite the considerable threats that are associated with echo chambers, research is currently limited to the emergence of echo chambers (Baumgaertner 2014; Flaxman et al. 2016; Nikolov et al. 2015; Vaccari et al. 2016) and the respective role of individual choice as opposed to platform’s recommender algorithms (Bakshy et al. 2015; O'Hara and Stevens 2015), psychological motivations of forming an echo chamber (Boutyline and Willer 2017), communication patterns within and across echo chambers (Grömping 2014; Liao and Fu 2014; Williams et al. 2015), predicting partisanship through echo chambers (Colleoni et al. 2014), and consequences of echo chambers on climate policy discussions (Jasny et al. 2015). Research has not yet conclusively attempted identifying different kinds of echo chambers let alone conspiracy chambers (O'Hara and Stevens 2015). In order to overcome the apparent knowledge gap we investigate *what social media echo chambers exist as well as whether and how conspiracy echo-chambers can be distinguished?*

We approach this research question by analysing the patterns of media consumption of over 7,000 users on Facebook. Thereby, we will provide three considerable contributions. First, we will identify different types of Facebook echo chambers. Currently, related research has adopted the oversimplified perspective of the two party system (i.e. democrat or republican) (Bakshy et al. 2015; Boutyline and Willer 2017; Colleoni et al. 2014). Due to their unique relevance, we focus particularly on the effects of conspiracy sites. Second, we will understand distinguishing characteristics in communicative behaviour of the conspiracy groups on Facebook. This is important since previous findings relied on survey (Jasny et al. 2015; Vaccari et al. 2016), web browsing (Flaxman et al. 2016; Nikolov et al. 2015) or experimental data (Liao and Fu 2014), and only applied to very specific Facebook groups (Grömping 2014) or Twitter hashtag topics (Williams et al. 2015). Third, we assess unique characteristics of users in conspiracy echo chambers. Since echo chambers have been found to rather result from individual decisions on which kind of content to consume than from the platforms’ recommender algorithms (Bakshy et al. 2015; Flaxman et al. 2016), this will help identify risk factors and build an understanding of who is particularly susceptible to conspiracy news.

2 Theoretical Background

We draw on social identity theory, which has been researched extensively across various scholars (Stryker and Burke 2000). Social identity on a collective level focuses on how identities rise from a membership of social groups (Henri and Turner 1986). It is argued that individuals like to become group members of a certain group and start to behave in a way which is appropriate for the group. If the group is relevant to them, they will suppress their individuality and focus on their social identity within the group. This process is also known as depersonalization (Carter 2015; Stets and Burke 2000). This phenomenon can also be seen in the case of echo-chambers, in which individuals either try to fit into the social environment of the chambers, or the rules forbid every action which contradicts the group's norm. Therefore, due to this conformity, ideas or ideologies are leveraged (Sunstein 2002), which explain the polarization in echo-chambers. The initial emergence of echo chambers is commonly explained through ideological and political homophily and contagion (Colleoni et al. 2014). Homophily describes the principle that similarity breeds connection and structures network ties. Consequently, people's personal networks become socio-demographically, behaviourally, and interpersonally homogeneous. This limits people's social worlds with powerful implications for their information reception, attitude formation, and interaction experiences (McPherson et al. 2001).

There is various IS research which identified the existence of echo chambers and how individuals engage with information on social media. Shore et al. (2016) investigated how divers Twitter users seek information via their followers. They wanted to answer the question whether users are encapsulated in echo-chambers and found that for the average account is linked more often to moderate news sources. However, there is a tiny network core which shows evidence of polarization and due to their strong activity and popularity this portion can explain the perception that social media incorporates widespread echo-chambers. Bessi (2016) targeted echo-chambers on Facebook and showed that users with similar psychological profiles engage in pseudo-scientific echo-chambers. Furthermore, it is shown that the participation in said echo-chambers in return has an effect on the psychological profile. It is argued that if users show low extraversion, high emotional stability, low agreeableness, low conscientiousness and high openness, there is a high likelihood that people will engage in pseudoscientific or conspiracy-like narrative. These profiles were extracted from their digital footprints, such as their language used on social media.

Bakshy et al. (2015) investigated how Facebook users may engage in cross-cutting content in the context of liberal, moderate and conservative content. 10.1 million Facebook users were examined and their interaction with socially shared news. They found that conservatives have a 17% risk ratio on clicks on cross-cutting content, while liberals have a ratio of 6%. This is due to a higher amount of shared news from the conservative side. The authors argue that the consumption of cross-cutting content is highly dependent on the user's friends and the algorithm which sorts the news feed on Facebook.

Echo chambers in general only provide limited and therefore insufficient information to their community basis. This leads to a selective exposure of the participating individual (Messing and Westwood 2014). Echo chambers in the context of conspiracy theories are especially dangerous because they lead to opinion polarization and even radicalization in a stronger degree (Dandekar et al. 2013). Radicalization can already occur by firmly believing that a position that is within the political mainstream is not just the best but that any other choice would be catastrophic. Social media help with this radicalization by encouraging group think, affecting the perceptions of identity and group membership (Sunstein 2018)**.**

Due to the particular uniqueness of conspiracy theorists that are far away from common public opinions, we expect even stronger homophilic tendencies to occur. This is especially harmful since conspiracy beliefs are particularly extreme and lead to a stronger seclusion from society and encourage socially destructive actions (e.g., terror attacks, political disengagement, and discriminatory behaviour). Due to the mentioned threats of conspiracy echo-chambers, we want to identify said echo-chambers with their specific characteristics, and investigate risk factors under which circumstances individuals are prone to becoming part of such communities.

3 Method

3.1 Data Collection

First, we collected a sample of Facebook user profiles. For this purpose, we began collecting profiles starting from a random Facebook profile page with a public friend list, which was then copied into a database. Afterwards, we copied the first public friend lists of the profile with the lowest Facebook-issued account number. To avoid a sample bias by restricting profile collection to a particular demographic class, we continuously repeated this process with the newly downloaded friend list and so forth. Ultimately, we collected a list of 170,000 user profiles. In a second step, we collected the individuals' Facebook likes. To avoid dispositional biases regarding selective information disclosure (e.g., only profiles that publicly disclose all information – i.e. friends and likes), we checked all profiles in our database for public like-items and profile information irrespective of whether or not they had previously disclosed friend lists. We collected public likes from almost 7,000 individual users resulting in a total of 1,450,000 likes and 280,576 unique items with averagely 207 items per profile (figure 1). The individual's data privacy was protected by omission of the user name and only using the internal Facebook ID to match profile and like information. Thereby, personal identification based on the publicly available information is rendered highly unlikely.

To further inform our data, we collected the political leanings (i.e., right, lean right, center, lean left, left, pro science, conspiracy-pseudoscience, questionable, and satire) for 1,846 political sites from AllSides (AllSides 2018a) and Media Bias-Fact Check (Media Bias/Fact Check 2018e).

work	education	current city	hometown	birthday	gender	Interested in	languages	religious viev	political views	relationship
Nike -> Resto	Rust College ->	Holly Springs,	Greenwood,	Apr 08	Male	Women	American E	Baptist	n/a	Single
n/a	n/a	Macon, Georgi	Macon, Georg	October 26	Female	n/a	n/a	Baptist	Democratic Pa	Single
n/a	n/a	Roanoke Rapi	n/a	Aug 20	Male	n/a	n/a	Baptist	n/a	n/a
n/a	n/a	Salinas, Califo	Columbia, So	n/a	Female	Men	English lar	Baptist	n/a	n/a
n/a	n/a	Seattle, Washi	East Lyme, Co	n/a	Male	n/a	n/a	Bible Believ	Conservative	Married
n/a	n/a	Little Rock, Ark	n/a	January 22	n/a	n/a	n/a	Christian	n/a	Single
n/a	Bishop State C	Toulminville, A	Toulminville,	Aug 09	Male	Women	n/a	Christian	n/a	In a relatic
n/a	n/a	Walnut Cove, N	Winston-Sale	June 23, 19	Female	n/a	English lar	Christian	n/a	Married si
Pepsi -> Sales	n/a	Stone Mountai	Decatur, Geo	September	Male	Women	n/a	I believe in	Conservative	n/a
n/a	Alcee Fortier S	Oakland, Calif	New Orleans,	Aug 07	n/a	n/a	n/a	It's all abou	Whatever mak	n/a
n/a	n/a	New York, New	Wilmington,	Sep 24	Female	Men	n/a	n/a	Liberal (politi	n/a
Boeing Comm	University of W	Seattle, Washi	Miami, Florid	n/a	Male	Women	n/a	Catholic (ch	Liberal (politi	Single
Hartsfield-Ja	Westside High	Atlanta, Georg	Macon, Georg	n/a	Female	Men	French	n/a	n/a	n/a
n/a	n/a	Atlanta, Georg	Kingston, Jam	n/a	n/a	n/a	English lar	n/a	n/a	n/a
n/a	University of C	Aurora, Colora	Denver, Color	June 29	n/a	n/a	English lar	n/a	n/a	n/a
n/a	n/a	Austin, Texas	Utica, New Yo	n/a	Female	n/a	American E	n/a	n/a	n/a

id	name	category
11128130	Tattoos	Art Gallery
10837998	Baseball	Interest
10375850	Coffee	Coffee Shop
11522748	Concerts	Arts & Entertainment
10217301	Mudding	Book
10373863	Country music	Performing Arts
10219201	Motorcycles	Sport
10379919	Flip-flops	Local Business
11208216	Dustin Pedroia	Athlete
11066029	Red Sox	Interest
22821786	Sweet Life	Ice Cream Shop
47326097	Piphany/Honey	Clothing (Brand)
18881982	The Treehouse	American Restaurant
95971371	UNION Restaura	American Restaurant
17711789	Very Jane	Website
79745822	Beyond Your Blc	Reference Website

Figure 1. Raw data sample excerpt of user profile (left) and like item information (right).

3.2 Data Processing

From the over 280k like items, we initially select all potentially relevant items with regard to our research objective. Thus, we selected 2,607 Like items from any of 24 manually identified potential news categories (e.g., News*, Politic*, Government*). Subsequently, we conducted a soft match between the user-generated coding from AllSides and Media Bias-Fact Check with the media items included in the data sample. In total we were able to identify the political leaning for 2,136 unique items (Table 1).

With regards to our research question, we wanted to further inform the types of conspiracy categories (Table 2). Thus, we selected all items from "conspiracy-pseudoscience" and "questionable", reviewed and discussed the different types of conspiracy sites among the authors, manually coded all distinct items and discussed the few deviations until we found agreement (Krippendorff 2004; 2012). Due to their focus on conspiracy concepts, we decided to combine the two conspiracy-pseudoscience and questionable categories into the general "conspiracy" category.

Political Leaning	Description (Sources, e.g., in favour of)	Examples	N (%)
Left	Government services, tax increases on the wealthy or keeping abortion legal (AllSides 2018f).	VICE, HuffPost	435 (20.37)
Lean Left	Federal laws to protect consumers, the environment and equal rights (AllSides 2018d).	BBC, The Guardian	734 (34.36)
Center	Does not systematically show opinions favoring either end of the political spectrum (AllSides 2018b).	Reuters, Financial Times	281 (13.16)
Lean Right	Decreasing government involvement in economic issues, taxes, and federal regulation in general (AllSides 2018e).	The Telegraph, New York Post	141 (6.6)
Right	Outlawing abortion, government should be as small as possible, traditional family values (AllSides 2018c).	CBN, Fox News	250 (11.7)
Pro Science	Legitimate science or are evidence based through the use of credible scientific sourcing (Media Bias/Fact Check 2018b).	CNET, National Geographic	183 (8.57)
Conspiracy-Pseudoscience	May publish unverifiable information that is not always supported by evidence (Media Bias/Fact Check 2018a).	InfoWars, Anonymous,	38 (1.78)
Questionable	Exhibits one or more of extreme bias, overt propaganda, poor or no sourcing and/or is fake news (Media Bias/Fact Check 2018c).	Qpolitical, Truth Examiner	63 (2.95)
Satire	Exclusively use humor, irony, exaggeration, or ridicule to expose and criticize stupidity or vices (Media Bias/Fact Check 2018d).	The Onion, New Roman Times	11 (0.51)
Notes. Number of unique news sites = 2,607; number of coded news sites = 2,136			

Table 1. Data sample of leaning-coded news sites on Facebook.

Furthermore, research has indicated that the communication style alternates between democratic and republican echo chambers (Grömping 2014; Liao and Fu 2014; Williams et al. 2015). To properly understand the differences between the various echo chambers, we assess the communication behaviour that has been discussed in the context of Fake News (Janze and Risius 2017) (Table 3).

Conspiracy Categories	Description	Examples	N (%)
Political Left	Propagating an extreme left agenda with dubious information.	Go Left America, Liberal Speak	13 (12.87)
Political Right	Propagating an extreme right agenda with dubious information.	InfoWars, Britain First	41 (40.59)
Political Establishment	Outspoken distrust in information and activities from governmental agencies.	Anonymous, Truth And Action	12 (11.88)
Media Establishment	Outspoken distrust in information from established media.	Uncensored News, Counter Current News	13 (12.87)
Environmental	Propagating a one-sided environmentalist agenda.	EcoWatch, REALfarmacy	3 (2.97)

Supernatural	Distributing information on supernatural occurrences.	Ancient Code, Awareness Act	5 (4.95)
Conspiracy Categories	Description	Examples	N (%)
Niche Interest	Advocating niche interests with dubious information	Native Americans, Clarion Project	3 (2.97)
National Interest	Propagating extreme nationalist agendas.	Behold Israel, Nos Comunicamos	5 (4.95)
Religious	Propagating religious beliefs.	Christian Science Monitor, Jews News	6 (5.94)
Notes. Number of Conspiracy news-sties = 101			

Table 2. Detailed categorization of conspiracy sites based on their predominantly expressed opinions.

Communication Variable			Description	References
Account		Rating	Average of five point rating	(Cao et al. 2011; Ghose and Ipeirotis 2011; Hu et al. 2012)
		Followers	Number of followers	(Clark and Melancon 2013; Risius et al. 2016)
		Likes	Number of likes	(Kosinski et al. 2013; Risius et al. 2016)
Post Content	Title and Message	Post Frequency	Number of posts per day	(Risius and Beck 2015; Risius et al. 2016; Shahbaznezhad and Tripathi 2017)
		Content Type	Share of media type (picture, video, article)	(Shahbaznezhad and Tripathi 2017)
		Word Count	Number of words	(Mudambi and Schuff, 2010; Pan and Zhang, 2011; Korfiatis, García-Bariocanal and Sánchez-Alonso, 2012; Cheng and Ho, 2015; Zhiwei Liu and Park, 2015; Park and Nicolau, 2015; Fang, Ye, Kucukusta and Law, 2016; Qazi et al., 2016; Salehan and Kim, 2016)
		Polarity	Average sentiment	(Mudambi and Schuff, 2010; Ghose and Ipeirotis, 2011; Salehan and Kim, 2016; Yin, Mitra and Zhang, 2016)
		Loudness	Share of capitalized letters	(Cao, Duan and Gan, 2011; Park and Nicolau, 2015).
		Readability	Flesh-Kincaid Score	Mudambi and Schuff, 2010; Cao et al., 2011; Ghose and Ipeirotis, 2011; Korfiatis et al., 2012; Fang et al., 2016)(DuBay 2004)
		Citations	Whether or not contains quotation	(Ayeh 2015; Liu and Park 2015; Park and Nicolau 2015; Zhang et al. 2014)
		Questions	Whether or not contains question	(Seebach 2012; Siering et al. 2014)
Community Responses		Likes	Average number of "likes" per post	(Kosinski, Stillwell and Graepel, 2013)
		Shares	Average number of "shares" per post	(boyd et al. 2010; Janze and Risius 2017; Risius and Beck 2015; Vosoughi et al. 2018)
		Love	Average number of "love" per post	(Hyvärinen and Beck 2018; Risius and Akolk 2015; Risius et al. 2015)
		Wow	Average number of "wow" per post	
		Haha	Average number of "haha" per post	
		Sad	Average number of "sad" per post	
		Angry	Average number of "angry" per post	

Notes. Data has yet to be collected

Table 3. Variables collected for the analysis of the communication behaviour of news sites.

Lastly, research has shown that echo chambers predominantly depend on the individual's choices much more than the platforms' content recommender algorithms (Bakshy et al. 2015; Flaxman et al. 2016). Most work on homophily has focused on similarities such as age, gender, and race. Sunstein (2018) even assumes that people form echo chambers that overcome more immediate attractors of demography and physical proximity through a shared ideology or religion, for example (O'Hara and Stevens 2015). To acknowledge the individual's effect on echo chambers, we consider the user characteristics to predict membership to a particular echo chamber (Table 4). This will help identify whether there are certain demographic and educational predispositions for joining echo chambers and could ultimately help develop more targeted counter measures to prevent radicalization. These different characteristics have been manually coded where applicable (i.e., current location, hometown, education, work, skills) and properly transformed (i.e., gender, age, political and religious views).

Characteristics	Coding
Gender	User specified (71 categories)
Age	5 year periods from 18 onwards
Location	Urban or rural (binary)
Hometown	Urban or rural (binary)
Education	International Standard Classification of Education (ISCED-97) (6 Levels)
Work	International Standard Industrial Classification (ISIC 4) (22 categories)
Skills	International Standard Industrial Classification (ISIC 4) (22 categories)
Languages	Number of languages specified by user
Political Views	User specified
Religious Views	User specified

Table 4. Individual user characteristics used to explore differences between group members across echo chambers.

3.3 Further Analysis – Next Steps

Before conducting the final analysis, we need to gather and transform the remaining data on the communicative behaviour of the individual sites. Thus, we are currently collecting the respective data from the different news sites. Since only the past 10 posts are immediately accessible through the public API, we will draw on those posts to approximate the general communication behaviour.

To understand the general media landscape on Facebook we conduct a Bayesian matrix factor analysis based on the news sties co-occurrences within the data sample. After having identified the proper number of factors that distinguish the media landscape, we apply a multi-dimensional scaling analysis on the dissimilarities of the items to determine the number and composition of echo chambers on Facebook (Figure 2). We operationalize echo chambers as the common patterns of consumed information sources actively established through Facebook Likes. Subsequently, we apply a latent class analysis to the communicative behaviour and conspiracy categories to determine differences between echo chambers. Lastly, we test individual user differences between groups through a decision tree and another latent class analysis.

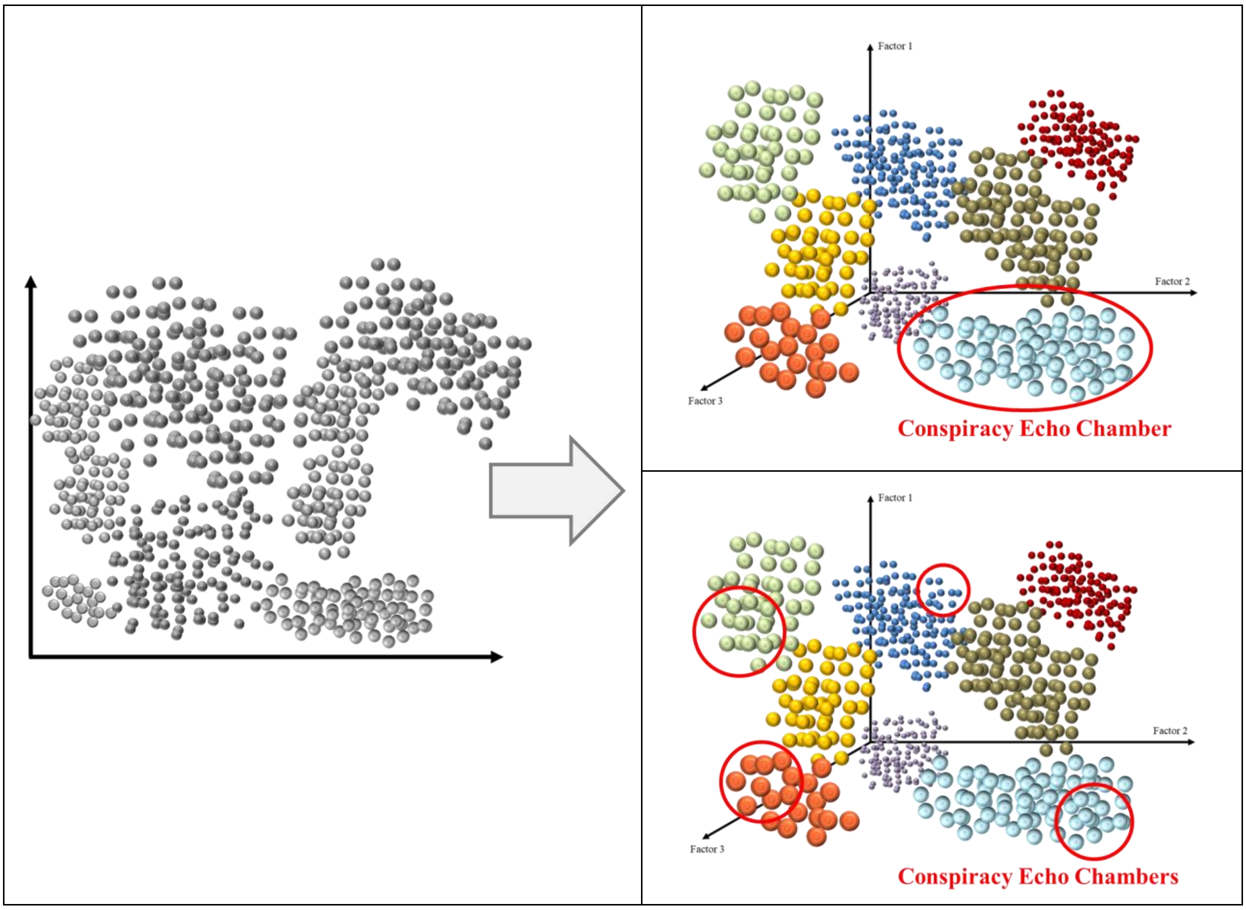

Figure 2. Conceptual data transformation from raw data sample to identifying potential social media echo chamber(s).4

4 Conclusion

Echo chambers are informationally encapsulated environments personalized to the singular users' interests (Nagulendra and Vassileva 2014). They are considered to be a major threat for modern society and democracy as they lead to polarization and even radicalization (Dandekar et al. 2013; Sunstein 2018). Echo chambers result from the homophilic desire to build connections with similar and likeminded people (McPherson et al. 2001). Particularly online social networks have been found to play a strong role on this radicalization (Hamm and Spaaij 2015). Research is currently strongly limited, for example, to artificial experimental settings or subjective self-report measures, the oversimplified binary distinction between Republicans and Democrats. Thus, we comprehensively collect real world data from 7,000 Facebook users and analyse general media consumption patterns across 2,137 news sites to identify the actual echo chambers. In this regard, we are particularly interested in the distinguishing characteristics of conspiracy echo chambers, which serve as a breeding ground for fake news (Sunstein 2018). We will be able to make three distinctive contributions: First, we will identify different types of Facebook media consumption groups beyond left- and right-wing groups. Second, we help understand distinguishing characteristics in communicative behaviour of the conspiracy groups on Facebook to identify them more easily. Third, we assess unique characteristics of users in conspiracy echo chambers to identify target or high-risk individuals for potential counter measures.

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