Influencers and targets on social media: Investigating the impact of network homogeneity and group identification on online influence

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Abstract

This study identifies social media users who aim to influence others and those who have experienced influencing behavior targeted at them. It investigates how influential users and targets of influence differ with respect to their demographic backgrounds and how the perceived group identification, network homogeneity, and size of the social network affect online influence. The data was based on a large-scale survey of Finnish people (N=2,761). We find that young and highly educated men were more likely to be targets of influence, but the demographic differences were less obvious with regard to influencing behavior. Moreover, group identification was a significant factor underpinning online influence for both influencing behavior and target experiences. The network homogeneity and the size of the network increased the likelihood of influencing behavior. Our main contribution is to shed light on people who are targets of online influencing on social media. By comparing influential users and their targets, this study extends the previous research, which has mostly focused on detecting influential people.

Contents

1. Introduction

Social media has become a powerful tool for disseminating information to influence people's opinions and behaviors. Popular social media accounts reach large audiences, and recently, professional brand *influencers*, who have the power to affect consumers' behavior and choices, have emerged online. Another primary domain in which influencing behavior has been frequently observed is online political communication. In social media people are increasingly exposed to political information and opinions of people in their networks, which creates a potential space for political persuasion to take place (Gil de Zúñiga *et al.*, 2018; Weeks *et al.*, 2017; Diehl *et al.*, 2016). Social context and particularly messages received from one's peer group play a key role in the formation of political views (Diehl *et al.*, 2016). Social media has proved to be useful for carrying out political campaigns by, for instance, increasing people's knowledge and discussion about relevant topics (Nisbet and Kotcher, 2009). Nevertheless, social media also provides a platform for disruption and disinformation which may have serious societal implications (Bennett and Livingston, 2018), for instance, when harmful content is propagated in order to influence public opinion and people's voting decisions in the run-up to elections (Ferrara, 2015, 2017). Therefore, it is essential to understand how information is propagated and reveal the mechanisms behind online influence. Identifying influential users can help administrators to implement appropriate interventions if necessary (Bakshy *et al.*, 2011; Mahmud, 2014). As a result, influencer identification has become a significant subject of research, and scholars have developed various techniques for the detection of such individuals (Huang *et al.*, 2013; Mahmud, 2014; Rosenthal and Mckeown, 2017).

Social media has accelerated the flow of information, and recent studies have also confirmed that misinformation and other problematic content spreads online uncontrollably, even faster than factual information does. Peer influence plays a crucial role in this dissemination because people prefer to share novel and emotive content, which they assume will interest their peers (Lewis, 2018; Vosoughi *et al.*, 2018). Social media users tend to disregard politically neutral and conciliatory viewpoints (Garimella *et al.*, 2018). Social networks, the key structural element of social media, are ideal for fostering social dissent; therefore, understanding peer influence is critical in the fight against misinformation and other problematic online content.

Ever since its emergence, social media has excited researchers because of its potential for collective action, and it has thus contributed to increased democratic and civic participation (Wolfsfeld *et al.*, 2013). One of the reasons why social media reflects democratic principles, such as equality and transparency, is the critical role of user-generated content and its assumed authenticity (Keegan and Gergle, 2010). However, lack of transparency is one of the main problems affecting online influence: if ordinary social media users are exposed to campaigns and information operations without knowing it, they may lack the means to realize when they are being systematically influenced for the benefit of commercial organizations or politicians. Therefore, it is critical to examine whether these, sometimes rather idealistic, views of social media as a liberating and democratizing socio-technological innovation have truly been actualized or whether social media has created new, covert, and more complicated mechanisms for information control and consequently, power distribution.

2. Theoretical background

2.1. Determining influence

Social influence research originates from the social sciences. In an analysis of the presidential election in 1940, Lazarsfeld and colleagues introduced a two-step model of information. They found that political information is diffused via a two-step process, the first step involving politically-informed opinion leaders and the second step, less-informed opinion followers (Lazarsfeld *et al.*, 1948). The opinion leaders have a dominant role as information brokers who are passing messages to their less-informed fellow citizens. They can shape public opinion by informing their peers about relevant topics and, in this way, alter their behavior and preferences (Nisbet and Kotcher, 2009).

The theory of social influence developed by Kelman (1958) suggests that individual behavior is influenced through three social processes: compliance, identification, and internalization. In other words, social influence occurs when an individual is complying with the opinions of significant others, developing an emotional attachment and feelings of belonging to a group, and accepting that influence by adopting the values and opinions of group members. In the context of online social networks, all these three modes of social influence apply to users' intentions of, and participation in, social action (Cheung and Lee, 2010; Zhou, 2011).

In the era of social media, dissemination of information has become more complex and social networks that facilitate this dissemination have become increasingly significant and widespread. Recently, researchers have begun to utilize large-scale network datasets to identify influencing behavior. Several measures have been used to detect online influence, such as dissemination of content (Bakshy *et al.*, 2011; Cha *et al.*, 2010), network quality (Huang *et al.*, 2013), and the number of followers and mentions containing a user's name (Cha *et al.*, 2010). Some research has made predictions of influencing behavior based on users' previous activities (Mahmud, 2014). Qualitative indicators of influence have also been identified, which reveal behavioral patterns typical of influencers based on the natural language they use in social media discussions (Rosenthal, 2014; Rosenthal and Mckeown, 2017). However, despite a great variety of emerging research techniques, detecting influencers is not an easy task. Research has shown that influencers are rare, with most conversations having only one or zero influencers (Rosenthal, 2014) and the *targets* of influencing behavior, the *influenced*, are even rarer (Aral and Walker, 2012).

Some critical gaps exist in the existing studies relating to influence detection. First, the methods used can only detect influencers after they have shown obvious signs of influencing others (Mahmud, 2014). Second, there is some controversy among researchers concerning the traditional model of behavioral contagion, which holds that influential individuals are the driving force for peer influence. There is also evidence to suggest that susceptibility to influence is the key trait behind social contagion (e.g. Aral and Walker, 2012; Centola and Macy, 2007). Furthermore, the composition of influencers' and susceptibles' networks seem to play a role in successful influence (Huang *et al.*, 2013). There is a need for research that extends our understanding of online influence by, for instance, explaining to what extent influence, or susceptibility to influence, drives social contagion, and what contextual factors contribute to it.

2.2. Characteristics of influencers

Research has found that influencers have several traits and behaviors in common. In general, opinion leaders are described as engaged and competent individuals who are viewed as honest and trustworthy by opinion followers, with whom they frequently interact (Turcotte *et al.*, 2015). They pay close attention to the topic in question, frequently discuss it with opinion followers, and consider themselves to be persuasive in convincing others to adopt an opinion (Lazarsfeld *et al.*, 1948; Nisbet and Kotcher, 2009). However, opinion leaders do not necessarily hold a powerful position. Rather, they hold a similar social position to those they aim to influence, but they are perceived as knowledgeable about the topic in question, possess diverse social networks, and have frequent discussions within those networks (Katz, 1957; Katz and Lazarsfeld, 1955; Nisbet and Kotcher, 2009). Opinion leaders tend to possess several desirable attributes relating to personality, expertise, or networks, including credibility, knowledge, enthusiasm, connectivity, and centrality (Bakshy *et al.*, 2011; Katz, 1957). Network size is usually a good indicator of popularity, but does not, in itself, reveal how influential a user is: popular social media accounts do not necessarily generate significant interaction in terms of audience engagement (Cha *et al.*, 2010).

Investigation of their natural language used in online discussions has revealed that influencers tend to be polite and friendly towards others, and vice versa: writing comments that include negative words indicates that an individual is less likely to be an influencer (Mahmud, 2014; Rosenthal, 2014). Positive comments and compliments are more likely to increase reciprocity and agreement between people because they increase a person's likability (Rosenthal, 2014). Overall, friendliness and reciprocity help to influence a large number of others because people are more likely to be influenced by someone they like. However, when influence takes the form of offering friendly advice and recommendations, its targets may remain unaware of the influence (Weimann, 1994).

Using Facebook profile information, Aral and Walker (2012) analyzed the backgrounds of people who sent and received influence-mediating messages. Unlike the majority of studies, they also considered susceptible users; namely, those who made productadopting decisions based on messages received from others. They found several differences between these two groups. First, susceptibility seemed to decrease with age, so that younger people were more susceptible to influence than older people. Second, men were more influential than women, but women influenced men more than they influenced other women. According to the same study, some differences also existed in network composition, since influential users tended to cluster together, suggesting that influential people with influential friends may have ulterior motives for befriending them since they aim to the spread information effectively. As for social media activity, those individuals who view themselves as opinion leaders tend to be highly engaged social media users and contributors who use various social media tools (Weeks *et al.*, 2017). Even though previous research has viewed influencers as somewhat exceptional, it is noteworthy that ordinary social media users can gain influence, over time, through a concerted effort to create content that others find interesting (Cha *et al.*, 2010). This finding suggests that influence is not gained accidentally, but rather, through hard work and personal involvement.

2.3. Homophily and homogeneity

People are attracted to similarity when establishing connections with others, and this has become evident in the online context. The similarity of people's affective dispositions to topics is explained by two concepts: *homophily* and *homogeneity*. Homophily refers to people's tendency to establish social connections with those who are similar to them (Lazarsfeld and Merton, 1954). Many studies have pointed out that homophily between people is an important foundation for social networks in an online context, and social media friends share similar interests, tastes, political orientations, and even personality traits (Lewis *et al.*, 2011; Lönnqvist and Itkonen, 2016; Weng *et al.*, 2010). Recently, a study by Robles and colleagues (2018), regarding homogeneity on Twitter, revealed that the people who are most politically active are also the most homogenized in their affective dispositions to discussion topics. Increased political homophily and decreased cross-network contact are likely to lead to more extreme political opinions and behaviors, but individuals who possess extreme opinions also tend to be homophilic on social media (Boutyline and Willer, 2017). Research suggests that political behavior spreads faster and more effectively in networks with high homophily rates and the influence is stronger within dense and active networks (Boutyline and Willer, 2017). Homophilic networks thus provide an optimal composition for disseminating extreme political ideologies and activities.

Scholars hold different views on whether social media is diminishing the diversity of people's social networks by creating groups of like-minded people (Sunstein, 2001) or, rather, increasing it by extending social capital via so-called "weak ties" (Ellison *et al.*, 2007; Valenzuela *et al.*, 2009). Research on influence from the network diversity point of view suggests that, in general, people are more likely to be influenced by someone similar to them (Rosenthal, 2014). By contrast, in homophilic and homogenous networks, people are likely to have frequent interaction and denser networks, but also to be more likely to influence each other, which explains why the influence spreads so rapidly. In diverse networks, however, influencing others requires more effort, without the benefits gained from social similarity or dense networks (Huang *et al.*, 2013).

When analyzing how influence between people occurs, it is important to identify whether similarity results from friend selection by people who are alike, or from people who are friends becoming more similar over time. Some of the work has therefore distinguished the effects of peer influence and homophily in behavioral contagion (Aral *et al.*, 2009; La Fond and Neville, 2010; Lewis *et al.*, 2011). A longitudinal analysis of Facebook friends showed that people tend to befriend those with similar cultural tastes, but thereafter, not much exchange of tastes occurs between them (Lewis *et al.*, 2011). Homophily seems to account for the majority of online behavioral contagion, whereas the role of peer influence is less significant, suggesting that the effect of peer influence might be exaggerated (Aral *et al.*, 2009; La Fond and Neville, 2010). In summary, research clearly shows that homophily is a strong basis for relationships on social media, but less evidence exists regarding social influence and online behavioral contagion as explanations for the similarity between friends.

2.4. Group identity

Social networks are a crucial element of today's online media environment, and recent evidence shows that information consumption is less concerned with factually correct or incorrect information than identity as a group member (Lewis, 2018). Ever since the emergence of online communities, research has shown that they can provide their members with a strong sense of belonging and emotional attachment (Blanchard and Markus, 2004). The experienced sense of community positively affects people's lives by increasing satisfaction and involvement in community activities (McMillan and Chavis, 1986) and protecting people from stress, anxiety, and depression (Pretty *et al.*, 1994). In an online context, a sense of community and social support was found to be positively associated with well-being (Obst and Stafurik, 2010). When such a sense of community and affective bonding are received through an online system, it encourages a user to engage with it more frequently (Zhang, 2010). Originally, the theory of social influence (Kelman, 1958) suggested that group identification was an important predictor of influence: recognition from others is more important when it is received from the relevant community. Moreover, a strong group identity motivates an individual to conform to others' expectations and, as a result, change his or her behavior accordingly.

Research evidence is inconsistent regarding how strongly group identity and influence are connected in an online context. McMillan and Chavis (1986) defined a sense of community in a physical setting as being composed of four elements: membership, influence, integration and need fulfillment, and a shared emotional connection. Studies conducted in an online context indicated that feelings of influence (i.e., influencing other members or being influenced by them) seem to be weaker in online groups (Blanchard and Markus, 2004; Obst *et al.*, 2002). This is explained by the greater choice of membership in interest-based groups and the lesser need for influence and control over members (Obst *et al.*, 2002). It is also possible that members, over time, internalize online community norms so effectively that they are no longer aware of influence occurring in the community (Blanchard and Markus, 2004).

In today's high-choice media environment, peer recommendations have become a major criterion for information selection, and opinion leaders and influential users play increasingly important roles in the regulation of exposure to online content (Mutz and Young, 2011). When evaluating information credibility, people tend to rely on their social networks. For instance, the investigation of people's online news consumption behavior (Turcotte *et al.*, 2015) shows that, when determining the trustworthiness of a news story, it is extremely important who is sharing the story. People tend to rely on information which is recommended by a person whom they trust, to the extent that the same news is perceived as more trustworthy when recommended by a social media friend compared to when reading it on the original news site (Turcotte *et al.*, 2015).

Similarly, social networks and group identity are present in online political participation. The term *personalized politics* has emerged to describe how political participation can be a form of self-expression and group identification (Bennett, 2012). The rise of personalized politics is evident on social media, where people can share their personal thoughts and participate in a collective activity through their networks. According to a recent study for Alternative Influence Network on YouTube, one major reason for its impact was its ability to provide both influencers and audiences with an appealing, countercultural social identity (Lewis, 2018). The same study also showed that political influencers who aim their message at the young social media audience have adopted techniques familiar to influence marketing: they build trust and credibility by developing intimate relationships with their followers, thus providing them with a sense of community.

2.5. Research goals and hypothesis

Previous research on social media influence has remained rather asymmetric because it has focused primarily on influencers, their behavior, and the composition of their networks, while the targets of this activity, the influenced users, have received much less scholarly attention. In order to gain a more holistic perspective on the dissemination of behavioral contagion, this paper considers both sides of online influence: influencers and the targets of influencing behavior. Furthermore, it investigates how social network characteristics might predict the likelihood of being either an influencer or a target of influencing behavior.

Drawing on the findings of Aral and Walker (2012), we expect that influencers and targets will differ according to their demographic backgrounds. We hypothesize that:

H1a: Younger social media users are more likely to be targets of influencing behavior than older.

H1b: Men are more likely to be influencers than women.

Some social media network-related characteristics are also likely to affect online influence. Research has found that in larger groups, members receive more information and the exposure to information is faster (Halberstam and Knight, 2016). We assume that, the larger the network size, the larger will be the amount of influence that an individual is exposed to. Based on previous research (Aral and Walker, 2012; Lewis, 2018), we expect that social media users who want to influence others will tend to build a following through active social networking and thus possess bigger networks than those with no intention of influencing others. We hypothesise that:

H2a: Those with larger social media networks are more likely to be targets of influencing behavior.

H2b: Those who aim to influence others have large social media networks.

Evidence indicates that social network composition is connected to individual social media users' behavior (Aral *et al.*, 2009; Boutyline and Willer, 2017). According to the "echo chamber" argument, communities of like-minded individuals are likely to amplify existing beliefs and restrict the free flow of information (Sunstein, 2001). Earlier research has shown that particularly politically homogeneous networks are favorable for spreading behaviors that require normative pressure or social confirmation (Boutyline and Willer, 2017). Influencing is more difficult when it is targeted at individuals with high social diversity than when it is targeted at those with low social diversity (Huang *et al.*, 2013). Therefore, we expect that:

H3a: Homophily of social networks positively predicts influencing behavior.

H3b: Homophily of social networks positively predicts the likelihood of being a target of influencing behavior.

An experienced sense of community and identification with a group were found to be important for social influence in the context of online interaction (Zhou, 2011). When other group members are prominent, the recognition and feedback from them motivates an individual to conform to their expectations and change their behavior accordingly (Kelman, 1958). For influencers, motivation to use social networks may be driven by the networks' usefulness as a tool for exerting influence (Aral and Walker, 2012). Therefore, we assume that influential users have a weaker sense of community and weaker feelings of belonging than the targets. We state the following hypotheses

H4a: Targets have a strong group identification and sense of community.

H4b: Influencers have a weak group identification and sense of community.

3. Data and methods

The quantitative data used in this study was collected between December 2017 and January 2018 in Finland (author removed, 2018). Using a simple random sampling technique, the survey questionnaires were sent to 8,000 18–74-year-old Finnish-speakers who were selected from the Finnish Population Register Database. In total, 2,470 (30.9%) respondents answered the questionnaire by mail or by completing an online questionnaire.

To acquire observations from a sufficient number of social media users, the data were supplemented by 1,254 participants (also aged 18–74) gathered at the same time, using a similar questionnaire, from an online panel administered by a private research company (Taloustutkimus Inc.). The final data included a total of 3,724 respondents, of which 66 percent came from the probability sample and 34 percent from the nonprobability sample.

In this study, we focused exclusively on social media users, which means that we rearranged the data according to the usage of social media. Therefore, in the final analysis, we excluded the respondents who did not use social media at all, and analyzed only social media users, that is, 2,761 respondents (74%) of the total data. Even though the analysis sample represented the population of Finnish social media users reasonably well, older users were slightly overrepresented and, consequently, the data was post-stratified in terms of age distribution to correspond to the official population distribution of the social media users in Finland (Official Statistics of Finland, 2016). We also tested the potential response bias and sample error related to the differentiation of sample techniques by analyzing probability and non-probability samples separately.

3.1. Measurement and analysis techniques

In the survey, the focus was on respondents' social media use and related attitudes. The main aim was to find out how prevalent social media influence is as a phenomenon and to identify the demographic backgrounds of those who aim to influence others or who have experienced being a target of influencing behavior. Influence was measured with the following two questions: “I use social media in order to affect the opinions of others”, and “I feel that others are trying to affect my opinions through social media”. Both statements were rated using a five-point scale ranging from 1 “Completely disagree” to 5 “Completely agree”. In the analysis, these two questions were used as dependent variables. To ensure a sufficient number of observations for the estimations, the variables were recorded by collapsing values 1–2 into the category “Disagree”, 3 into the category “Medium”, and 4–5 into the category “Agree”.

In the first phase of analysis, we estimated how the two types of social media users (i.e., influencers and targets) differed in terms of their demographic backgrounds by considering the effect of sex, age, and education. The effect of age was determined by classifying participants into seven age groups: 18-26, 27-34, 35-44, 45-54, 55-64, and 65-74. The International Standard Classification of Education was followed with regard to the groupings for education. We also adjusted the effect of social media activity by controlling for participants’ social media use activity using a 5-point scale, including 1 “Never”, 2 “Sometimes”, 3 “Weekly”, 4 “Daily”, and 5 “Many times per day”.

In the second phase, the effects of social media networks were analyzed from different perspectives. First, we modelled whether the size of social media networks was associated with being an influencer and/or a target of influencing behavior. We measured the size of a participant’s social media networks using the initial question: “To what extent do you have friends and acquaintances on social media?” The answer options ranged from 1 “Not at all” to 5 “Very much”. This variable was normally distributed and was used as a continuous variable in the further analyses.

Thereafter, we predicted dependent variables according to two social psychological measurements (i.e., group identification and network homophily), and incorporated them into the research model as predictors. By following the formation recently validated by Kaakinen and colleagues (2018), we measured group identification with two statements: “I belong to social media communities or groups that are an important part of me” and “I belong to social media communities or groups that I am proud of”. The homophily of social networks was measured with a sum variable constructed of two statements: “On social media, I interact only with people with whom I share similar interests” and “I interact exclusively with people who are like me on social media”. Responses ranged from 1–7, with 1 being “Does not describe me at all”, and 7 being “Describes me completely”.

Table 1 provides descriptive information for all the applied variables.

Table 1. Descriptive statistics for applied variables.

	N	%	M	SD
Dependent variables:				
Target				
Agree	603	22.5		
Neither agree nor disagree	630	23.5		
Disagree	1,447	54.0		
Influencer				
Agree	309	11.5		
Neither agree nor disagree	567	21.2		
Disagree	1,804	67.3		
Independent variables:				
Man	1,283	47.9		
Woman	1,396	52.1		
Age = 1, 18–26	332	12.4		
Age = 2, 27-34	379	14.2		
Age = 3, 35-44	398	14.9		
Age = 4, 45-54	505	18.9		
Age = 5, 55-64	589	22.0		
Age = 6, 65-74	476	17.8		
Education = 1, Primary	234	8.4		
Education = 2, Secondary	865	32.5		
Education = 3, Bachelor	944	35		
Education = 4, Master	636	24.1		
Social media activity				
Never	503	18.8		
Sometimes	242	9.0		
Weekly	404	15.1		
Daily	1,291	48.2		
Many times per day	240	9.0		

The size of social media networks	2,723	2.9	0.9
Group identification	2,721	7.92	3.76
Network homophily	2,718	6.08	2.92

Notes.
N = Responses from social media users
M = Mean
SD= Standard deviation

3.2. Analytical strategy

The analytical strategy developed equations for each hypothesis:

H1a: P(Y1) = X1+ X2+X3+C1
H1b: P(Y2) = X1+ X2+X3+C1
H2a: P(Y1)= X4 +X1..X3+C1
H2b: P(Y2)= X4 +X1..X3+C1
H3a: P(Y1)= X5 +X1..X3+C1
H3b: P(Y2)= X5 +X1..X3+C1
H3a: P(Y1)= X6 +X1..X3+C1
H3b: P(Y2)= X6 +X1..X3+C1

Here the Y1 refers to the probability of being an influential social media user, and Y2 refers to the probability of being a target of influencing on social media. X1 stands for sex, X2 means age, and X3 refers to education. C1 means social media activity and it is used as a covariate throughout the modeling process. X4 means the size of social media networks, X5 refers to identification with social media networks, and finally, X6 stands for the perceived homophily in social media networks.

First, we compared the main characteristics of the dependent variables. Secondly, we performed ordered logistic regression (OLR) analyses using the Stata® 15.1 program. OLR is a suitable method for modeling the variation of dependent variables because it only concerns the order of the variable, without the need to satisfy an assumption of normal distribution. We present the coefficients with statistical significance. We also conducted a robustness check to test the similarity of effects in the probability and nonprobability samples.

4. Results

The empirical analysis began by analyzing both of the dependent variables descriptively. In other words, the direct effects of demographic factors on the likelihood of being an influencer or a target of influencing on social media were examined. In Figure 1, we present the results of the descriptive analysis.

First, we found that a total of 23.3 percent of Finnish social media users felt that others were trying to affect their opinions through social media; in other words, they felt they were targets of influencing behavior. We found that young men, and respondents with a master's education, were more likely to be exposed. Approximately 25 percent of male respondents, 30 percent of respondents with a master's education, and over 40 percent of respondents who were under 27 years old reported being a target of influencing behavior. In terms of the second dependent variable, we found that 11.4 percent of Finnish social media users reported using social media in order to affect the opinions of others; in other words, be an influencer. The demographic differences were similar to those for the first variable, but only marginally equivalent because the differences were slighter.

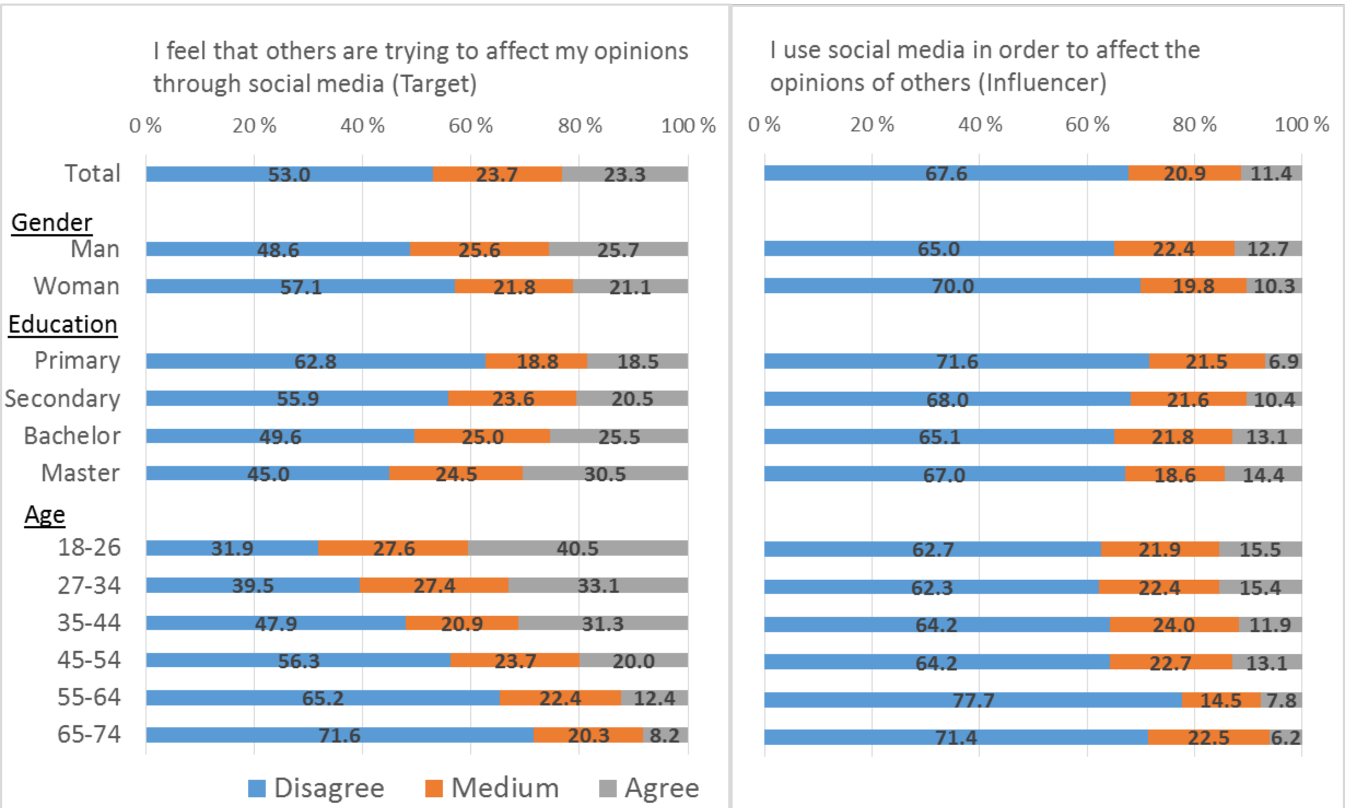

Figure 1. The distributions of the dependent variables by gender, education, and age.

The results of ordinal regression are shown in Table 2. The results partly supported hypotheses 1a & 1b, since the underlying demographics predicted social media users' likelihood of being influencers or targets. Men were more likely to be influencers or targets than women. The comparison of ages indicated that the group of 55–64-year-olds differed significantly from the youngest respondents (18–26 years) when the likelihood of influencing others on social media was analyzed. When considering respondents who reported having been a target of online influencing behavior, it was clear that this was particularly an experience of young social media users, since respondents under 27 years agreed most often with this statement.

Educational differences were also detected in terms of the probability of being influenced, since respondents who had a master's degree differed significantly from those who had a primary education. General activity on social media predicted both dependent variables positively. According to the robustness check (Table A1), the probability and non-probability samples yielded similar results regarding demographic differences.

Table 2. The likelihood of being an influencer or target according to age, sex, education, and social media activity. Ordered logit coefficients (coef.) with standard errors (se).

	Influencer		Target	
VARIABLES	Coef.	SE	Coef.	SE
Age = 1, 18-26 (reference group)				
Age = 2, 27-34	0.00	(0.16)	-0.47***	(0.14)
Age = 3, 35-44	-0.09	(0.16)	-0.70***	(0.15)
Age = 4, 45-54	0.08	(0.15)	-1.01***	(0.14)
Age = 5, 55-64	-0.43**	(0.15)	-1.34***	(0.14)
Age = 6, 65-74	-0.05	(0.15)	-1.63***	(0.15)
Sex (Woman)	-0.42***	(0.09)	-0.51***	(0.08)
Education = 1, Primary (reference)				
Education = 2, Secondary	0.13	(0.15)	0.12	(0.16)
Education = 3, Bachelor	0.16	(0.18)	0.19	(0.18)
Education = 4, Master	0.18	(0.17)	0.63***	(0.17)
Social media activity	0.42***	(0.04)	0.19***	(0.03)
Observations	2,738		2,718	
Pseudo R2	0.04		0.06	

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Next, we analyzed the extent to which users' social media networks and involvement in social media networks predicted their likelihood of being influencers or targets. The models presented below "Influencer" in Table 3 show the results of the first analyses, which focused on predicting the likelihood of being an influencer. We found that the size of social media networks, identification with social media networks, and perceived homophily of social media networks contributed positively to the likelihood of being an influencer. The results thus confirmed hypotheses 2b and 3a. However, we also expected that influential users would have weaker group identification, which was not confirmed by the analysis, and hence hypothesis 4b was rejected. The results of the robustness check supported this result, since differences between the samples were not found (Table A2).

The models presented below “Influenced” in Table 3 show that group identification contributed positively to users’ likelihood of being a target. However, there were no significant effects regarding the size of social media networks or perceived homophily in social media networks. The robustness check obtained generally similar results for both samples, but there were no significant sample differences regarding the effect of social network size. However, neither of the samples produced significant estimates (Table A3). These findings did not support hypotheses 2a and 3b, since neither extensive social media networks nor network homophily predicted the likelihood of being a target. Nevertheless, the analysis showed that the targets reported a strong group identification, thus confirming hypothesis 4a.

Table 3. The likelihood of being influencers or targets according to size of social media networks, group identification, and perceived homophily in social media networks. Ordered logit coefficients (coef.) with standard errors (se).

VARIABLES	Influencer Model 1	 Model 2	 Model 3	Target Model 1	 Model 2	 Model 3
Size of networks	0.30***			-0.03		
	(0.05)			(0.05)		
Group identification		0.16***			0.06***	
		(0.01)			(0.01)	
Network homophily			0.06***			0.00
			(0.01)			(0.01)
Observations	2,723	2,721	2,718	2,704	2,707	2,706
Pseudo R2	0.05	0.08	0.05	0.06	0.07	0.06

Ordered logit coefficients with standard errors in parentheses
Models adjusted for gender, age, education and social media activity
*** p<0.001, ** p<0.01, * p<0.005

5. Discussion

The findings show that influencers and targets do not differ with regard to their demographic backgrounds. In line with Aral and Walker (2012), we found that influencing behavior is more likely for men. Moreover, younger respondents under 27 years had more often experienced influencing behavior from others than the older respondents had, and those who were highly educated most often experienced influencing behavior targeted at them. The fact that young and highly educated people have strong social media skills, and are therefore better able to recognize influencing behavior, may partly explain these two findings.

The effects of network size and homogeneity seem to be different for influencers and targets. Against expectations, having large and homogenous social media networks does not increase the likelihood of being influenced, whereas it does increase the likelihood of influencing behavior. This indicates that those who aim to influence others might be more active in building social media networks. Similarly to previous research (Huang *et al.*, 2013), this study proposes that influencing behavior is easier in homogenous groups. According to the findings, group identification and a sense of community are important for both influencers and targets, and are thus major factors that contribute to online influence. Against expectations, it seems that also the influencers identify with their networks, so their participation in social media networks does not happen only for instrumental reasons.

This study has some limitations, the most obvious of which concerns the research method. Unlike previous studies, this study did not analyze signs of observable influence, but instead focused on the respondents' intentions and experiences. In the survey, the respondents were asked if they had felt that others were trying to influence them online. It is important to note that having experienced influencing behavior does not mean that the individual is susceptible. Moreover, being a target of influencing behavior does not mean that the influence has been successful, since the outcomes of these attempts are unclear. Undoubtedly, there are individual differences in how well people detect influence in their online environment, and high education levels and long experience of social media use are likely to be important factors explaining the recognition of influence.

In general, some drawbacks in relation to surveys as a method for detecting influence have been reported. Respondents may overestimate or underestimate the actual degree of influence in their social networks (Nisbet and Kotcher, 2009). In particular, measuring homophily with survey scales has been criticized for capturing only the perceived homophily. According to Boutyline and Willer (2017), measures that are derived solely from respondents' descriptions are likely to exaggerate the true level of homophily because people tend to overestimate their similarity to each other.

In addition to users' individual attributes, there are context-specific factors that affect online influence. Particularly, identification with social networks is a major factor behind online influence for both influencers and targets. Furthermore, having large and homogenous networks predicts the likelihood of influencing behavior. We suggest that future research should extend the focus from identifying characteristics typical of influencers to considering the social context in order to gain a broader understanding of online influence.

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Appendix

Table A1. The likelihood of being an influencer according to age, gender, education, and social media activity. Ordered logit coefficients (coef.) with standard errors (se)

	Probability		Non-probability	
VARIABLES	coef	se	coef	se
Age = 1, 18-26 (reference group)	a		a	
Age = 2, 27-34	-0.22	(0.20)	0.12	(0.28)
Age = 3, 35-44	-0.18	(0.19)	-0.07	(0.29)
Age = 4, 45-54	-0.10	(0.19)	0.16	(0.27)
Age = 5, 55-64	-0.54**	(0.19)	-0.43	(0.28)
Age = 6, 65-74	-0.23	(0.19)	0.05	(0.27)
Woman	-0.29**	(0.11)	-0.52***	(0.14)
Education = 1, Primary (reference)	a		a	
Education = 2, Secondary	0.08	(0.18)	0.12	(0.30)
Education = 3, Bachelor	0.04	(0.23)	0.21	(0.33)
Education = 4, Master	0.24	(0.21)	-0.00	(0.32)
Social media activity	0.34***	(0.05)	0.49***	(0.06)
Observations	1,736		1,002	
Pseudo R2	0.0343		0.0530	

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table A2. The likelihood of being influenced according to size of social media networks, group identification, and perceived homophily in social media networks. Ordered logit coefficients (coef.) with standard errors (se).

	Probability		Non-probability	
VARIABLES	coef	se	coef	se
Age = 1, 18-26 (reference group)	a		a	
Age = 2, 27-34	-0.40*	(0.18)	-0.78**	(0.26)
Age = 3, 35-44	-0.86***	(0.18)	-0.64*	(0.28)
Age = 4, 45-54	-1.10***	(0.17)	-1.13***	(0.26)
Age = 5, 55-64	-1.40***	(0.17)	-1.43***	(0.26)
Age = 6, 65-74	-1.67***	(0.18)	-1.78***	(0.28)
Woman	-0.43***	(0.10)	-0.51***	(0.13)
Education = 1, Primary (reference)				
Education = 2, Secondary	-0.13	(0.18)	0.66*	(0.32)
Education = 3, Bachelor	-0.04	(0.22)	0.69*	(0.34)
Education = 4, Master	0.48*	(0.20)	1.02**	(0.34)
Social media activity	0.17***	(0.04)	0.19***	(0.05)
Observations	1,736		1,002	
Pseudo R2	0.0343		0.0530	

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table A3. The likelihood of being an influencer according to the size of social media networks, group identification, and perceived homophily in social media networks. Ordered logit coefficients (coef.) with standard errors (se).

VARIABLES	Probability sample			Non-probability Sample		
	coef	coef	coef	coef	coef	coef
The size of network	0.27***			0.43***		
	(0.07)			(0.08)		
Group identification		0.13***			0.21***	
		(0.02)			(0.02)	
Network homophily			0.05**			0.08***
			(0.02)			(0.02)
Observations	1,724	1,719	1,717	999	1,002	1,001
Pseudo R2	0.0404	0.0592	0.0384	0.0682	0.109	0.0588

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05

Table A4. The likelihoods of being influenced according to size of social media networks, group identification and perceived homophily in social media networks. Ordered logit coefficients (coef.) with standard errors (se).

VARIABLES	Probability sample			Non-probability sample		
	Coef	Coef	Coef	Coef	Coef	Coef
The size of network	-0.09			0.12		
	(0.06)			(0.08)		
Group identification		0.05***			0.09***	
		(0.01)			(0.02)	
Network homophily			-0.02			0.02
			(0.02)			(0.02)
Observations	1,706	1,707	1,707	998	1,000	999
Pseudo R2	0.0677	0.0694	0.0674	0.0552	0.0653	0.0543

Robust standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05