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Sharing Political News Online: A Network Model of the Spread of Information on Social Media

Intersections. EEJSP
11(1): 40–62.
https://doi.org/10.17356/ieejsp.v11i1.1169
https://intersections.tk.hu

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Abstract

Social media plays a crucial role in online political campaigns as political parties can reach, inform, and mobilize voters through these platforms. Political campaigns share information on social media to mobilize support, and prior research shows that sharing content on social media correlates with the offline popularity of political parties. In this paper, we model the spread of political content on the internet. We start by exploring popularity and sharing behavior related to posts by Hungarian politicians on Facebook. We utilize this analysis to build an agent-based model. Within this, we test how echo chambers, homophily, and network structure affect the number of shares that contribute to information diffusion on social media. Our simulation compares spreading in different network structures and shows that preferential attachment models are not the most efficient for fostering diffusion in networks with relatively low density or when a filtering mechanism is present. Our model confirms that homophily generally has a positive effect on diffusion, especially within echo chambers. Echo chambers enhance the diffusion of political news with a limited potential audience. Furthermore, the results of our agent-based simulation indicate that homophily and echo chambers can significantly influence the spread of political content on social media, with echo chambers particularly enhancing diffusion in networks where overall diffusion is low.

Keywords: social media, political participation, agent-based model

1 Introduction

Political activity is any activity that is intended to or has the consequence of affecting, either directly or indirectly, government action (Verba et al., 1995). It can occur offline, in traditional forms – participating in demonstrations, contacting members of the government, signing a petition, etc. – or, as has become more common in the last few decades, via online platforms on social media sites.

Political campaigns utilize social media sites to engage voters and aim to mobilize them to share political content. For political parties, this seems to be an effective tactic for reaching their ultimate goal – winning elections – as recent research has shown that the number of shares on social media sites may correlate with the offline popularity of a political party (Bene, 2018).

The use of social media during political campaigns has been significant since 2006; political candidates have been using Facebook for political campaign purposes (MacWilliams, 2015), and it has become increasingly frequently used for the organization of political demonstrations (Koltai & Stefkovics, 2018). Magin et al. (2017) argues that political campaigning has three main functions: to disseminate information, to facilitate dialogue between politicians and voters, and to mobilize support.

Prior research has mainly focused on the mobilization aspect and investigated the relationship between online and offline participation (Feezell et al., 2016; Groshek & Dimitrova, 2011; Oser et al., 2013; Theocharis & Lowe, 2016). This paper understands mobilization as sharing content (Klinger, 2013; Magin et al., 2017) and focuses on information dissemination. The dynamics of information dissemination are modeled as the velocity of the spread of political content in various network scenarios. We analyze how characteristics of social media, such as the effects of reactions and comments to a post, network structure, political homophily, and algorithms that amplify echo chambers, may influence online information spread. For this purpose, we introduce an agent-based model based on observations of actual Facebook posts. The results of the model reveal several key findings about the role of network characteristics. In our analysis, small-world networks outperformed preferential attachment networks (Albert & Barabási, 2002) in terms of the number of shares, particularly when network density was low or constrained by filtering algorithms. This is because sharing is influenced by users' political alignment, which can hinder diffusion in highly centralized networks. Furthermore, in the model, homophily has varied effects depending on the network setting. In more connected networks with similar interests, posts spread extensively within that group but struggled to break out of it. Interestingly, in scenarios where diffusion was limited by content-filtering algorithms, homophily enhanced the spread of news, especially in small-world networks. Echo chambers also play a significant role in enhancing diffusion, particularly for news with a limited potential audience. When echo chambers are present, homophily positively affects diffusion by creating paths through which politically interested agents can be reached, even if they are distant in the network.

2 Theoretical background

Individuals can benefit from social connections, as they can access and use the resources of other individuals through them. Regarding politicians, this benefit translates into the opportunity to reach otherwise unrecognized people, thus lowering campaign costs (Valenzuela et al., 2018). This benefit, however, depends on whether online activities impact offline political outcomes.

In the light of previous empirical studies, the existence of this link is not evident. While some studies have demonstrated the tangible impact of social media on political participation, like on voting (Dimitrova et al., 2014; Holt et al., 2013), others have found that reliance on social networking sites had no effect on political participation, although it was related to civic participation (Zhang et al., 2010). Further positive findings include Skoric and Zhu (2016), using Singaporean data, while negative ones include Groshek & Dimitrova (2011), who found no significant impact of social media use on vote intention in the 2008 US presidential election and Theocharis & Lowe (2016), who demonstrated the negative effect (substitution) between online and offline political participation using an experiment on Facebook. To synthesize this mixed evidence, we can rely on a meta-analysis conducted by Boulianne (2020), who investigated this issue using over 300 studies from the past twenty years. The study revealed that despite significant cross-country variation, a positive relationship between online activity and offline political participation exists.

A key mechanism linking online and offline political activity is sharing political content. According to Magin et al. (2017), political campaigning has three main goals: to disseminate information, to facilitate dialogue between politicians and voters, and to mobilize support. Sharing content integrates voters into the campaign: it is a common, low-threshold, but potentially very effective mass-centered form of mobilization. Thus, sharing acts as the key micro-level link between online and offline forms of political participation on social media.

We know that social media connections emerge from distinct real-life social network structures (Vepsäläinen et al., 2017). However, the main attribute of these platforms is to create and display connections with others on a platform via a semi-public or public profile (Boyd & Ellison, 2007). Therefore, network structures can be substantially different across different media platforms and according to the different facets of the connections that are maintained offline. As news shared on social media may spread differently depending on the network structure (Pegoretti et al., 2012), the network structure behind the social media platform is a key factor in the analysis.

The increasing unavailability of large contemporary social media for research purposes, starting with Facebook and followed by X (ex-Twitter), however, restricts the current analysis of the global network structure of these platforms. Still, evidence from earlier studies suggests that the network structure of online social networks combines several features of basic models. Degree distributions in online social networks are definitely unequal, with a few people having many connections and many only a few. However, the former are not as unequal as preferential attachment (PA) models would suggest; rather, the best of the latter involve a hybrid process of random and preferential attachment (Corten, 2012). Further, they show a significant positive degree of assortativity (Corten, 2012; Ugander et al., 2011), which does not follow either from the random or the preferential attachment model (c.f. Barabási & Pósvai Ch. 7). They also involve significant clustering (Corten, 2012; Ugander et al., 2011), which again does not follow from the above models, but is a property of the small world model. A related property is that they exhibit a hierarchical structure in similarity, but two random people can still reach each other over a very small distance (Watts et al., 2012), otherwise known as the six degrees of separation.

Therefore, simulations usually also apply these types of networks to model social network sites: namely, preferential attachment networks, random (a variant of Erdős-Rényi model) networks, and small-world networks (Chan 2019, Jiang & Jiang, 2014).

The impact of network structure has been analyzed using different opinion dynamics and diffusion models. Pegoretti et al. (2012) found that information diffusion is faster in small-world networks than in random networks when information is not perfect, meaning that information is not known to all members of the network equally but spreads through the 'demonstration effect,' i.e., via contacting each other (broadcasting or marketing). Centola (2010) also found that the small world network involves ties that bridge long distances, and the former propagate/diffuse information in an experimental setting faster than in a lattice-structured network. In contrast, random networks perform faster when diffusing an innovation with an equal chance for each agent, who all have an idiosyncratic willingness to adopt (Pegoretti et al., 2012). Korkmaz et al. (2019) found that diffusion was generally faster on scale-free networks than on random networks.

We can assess different features of 'real ' social networks using these basic network models, albeit separately. Basically, they all generate relatively short distances (compared to the lattice approach). The preferential attachment mechanism creates hubs, while the small world network creates local cohesion (clustering). However, echo chambers are a central aspect of online politics that we cannot analyze with these network properties.

Echo chambers are defined as clusters formed by users with homogeneous content production and diffusion, in which one's beliefs are reinforced due to repeated interactions with individuals sharing the same points of view (Cota et al., 2019). Selective exposure (homophily) and confirmation bias are key mechanisms contributing to the formation of echo chambers (Quattrociocchi et al., 2021).

In networks, homophily is defined as the inclination of people to interact more with others with similar characteristics rather than with people with different ones. This emerges along two key social dimensions: status and values (Lazarsfeld & Merton, 1954; McPherson et al., 2001). From our perspective, the relevant dimension is value homophily, that is, whether people who are more aligned with a political opinion and, therefore, more likely to share it are more likely to be connected in the network.

A further element that may amplify echo chambers is the algorithms used by social media. Personalized recommender algorithms are routinely used by e-commerce and social media to filter content that fits the preferences of the user (Ge et al., 2020). Recommending friends on social media itself contributes to echo chambers if homophily is present (Cinus et al., 2022). In addition, the presence of content filtering according to the preferences of the user contributes to the positive feedback loop of echo chambers (Jiang et al., 2021).

As basic network models themselves do not create echo chambers, in order to analyze them in the model, we add these two features, homophily, and content filtering, to the model as additional mechanisms.

Previous studies have found that homophily significantly influences diffusion. Aral et al. (2013) found that the adoption of a new (instant messaging) service significantly decreased in real networks compared to reshuffled networks from which homophily was eliminated; thus, homophily decreased diffusion. Korkmaz et al. (2019) have shown that both homophily and heterophily are better than random assignment in terms of the speed and size of cascades in an observed network and a scale-free network model, but in random networks, homophily promoted diffusion. Simulation models have shown that social influence in opinion dynamics and echo chambers in the case of controversial issues leads to the polarization of opinions instead of developing a consensus and the segregation of the network into several separated communities (Baumann et al., 2020; Li & Tang, 2015).

Such dynamics of polarization have also been observed empirically on social networks (Del Vicario et al., 2016; Li & Tang, 2015). From the point of view of news sharing, such a polarized outcome may correspond to the limited diffusion of news, wherein the news reaches only that cluster of users who initially had favorable attitudes. Concerning the relationship between the diffusion of the news and recommender algorithms, Quattrociocchi et al. (2021) found greater segregation in news consumption on Facebook than in Reddit and larger biases in information diffusion due to the clusters on social media based on content curating algorithms that are not tweakable by users (Facebook, Twitter) in contrast to other platforms, e.g., Reddit. In the case of Facebook, they found that the user's attitude ('leaning') affects who the final recipients of the information are, thus increasing the polarization in information diffusion. Considering news sharing, therefore, we expect that a content filtering algorithm (based on preferences) itself will limit the diffusion of news sharing and that the negative impact of homophily and preference-based filtering algorithms may amplify each other.

To sum up, previous research has produced divergent conclusions about the impact of network structures on diffusion. However, the modeling assumptions were also heterogeneous. Therefore, our key research question is: How do the above-described results apply to the case of sharing political news online? Which network structures will be more efficient in our case? While we do not have a clear hypothesis concerning network structure based on the previous literature, with a focus on news sharing, it is anticipated that a content-filtering algorithm based on user preferences could potentially restrict the diffusion of news sharing. Additionally, we assume that the negative influence of homophily (individuals tend to connect with like-minded people) and preference-based filtering algorithms may amplify each other, leading to further limitations on the dissemination of political news.

3 Data and methods

3.1 Methods

To model information spread on networks, we use agent-based modeling (ABM). ABM, also named individual-based modeling, is a method of modeling dynamics in complex systems that is often used to study the emergence of macro-level phenomena from individual, micro-level interactions in the social sciences. In an agent-based simulation, agents are autonomous, interactive individuals who keep evolving by monitoring their neighbors' state through stochasticity or, as in sophisticated agent-based modeling scenarios, through artificial intelligence approaches (Helbing, 2012). ABM is also an appropriate and widely used methodology for modeling complex phenomena in various network architectures (Ylikoski, 2014), such as information diffusion and the relationship between online and offline political activity.

Agent-based models have the advantage of a high degree of flexibility; they are capable of including various simple or complex mechanisms of interaction across agents. This also means that the model specification needs external inputs and some theoretical guidance on building the interactions. For this purpose, we build on pre-existing models of diffusion and social influence. However, in order to get insights on how to apply them to our specific case, spreading political news, we also turn to an empirical examination of social media.

3.2 Data Analysis

To create an empirical starting point for our agent-based model, we analyze Facebook data about the political activity of Hungarian social media users. Of the two most popular current social media platforms that are used in politics, namely X (ex-Twitter) and Facebook, we chose Facebook because, in Hungary, Twitter is way less popular than Facebook. Bene and Somodi (2018) have shown that Hungarian politicians are typically available on Facebook.

In addition, although data was more readily available for analyzing Twitter usage, through the dedicated software tool Crowdtangle, Facebook's data was also made available for limited research purposes. Crowdtangle is a Facebook-owned tool that tracks interactions on public content from Facebook pages, groups, verified profiles, Instagram accounts, and subreddits. It does not include paid ads unless those ads began as organic non-paid posts that were subsequently 'boosted' using Facebook's advertising tools. It does not include activity by private accounts or posts made visible only to specific groups of followers, either.

For the analysis, the data collection period ran from January 21-22 (Friday-Saturday), 2021, and targeted seven Hungarian political parties and their leaders. Some of the parties had joint leadership; in these cases, pages for both leaders were included. The data covers every post these parties and party leaders created in the given period. The data also includes the number of reactions and shares associated with each post in consecutive timesteps. The last timestep is the 74th, which marks that at least 20 days have passed since the original post.

During the campaign, several parties from the opposition formed an electoral alliance and have been campaigning together since the end of 2020. The electoral alliance was made up of six political parties: Demokratikus Koalíció – DK (Democratic Coalition - DK); LMP – Magyarország Zöld Pártja (LMP – Hungary's Green Party); Jobbik Magyarországért Mozgalom (Jobbik - Movement for a Better Hungary); Momentum Mozgalom (Momentum Movement); Magyar Szocialista Párt – MSZP (Hungarian Socialist Party – MSZP); and Párbeszéd Magyarországért (Párbeszéd – Dialogue for Hungary). Polls measured this alliance's popularity as increasing, closing in on the incumbents' popularity (Közvélemény-kutatók.hu).[1] However, this electoral alliance was a loose formation, and the participating parties decided to hold a primary in late 2021 to select a final candidate to run for the office of the Hungarian Prime Minister in 2022. Thus, parties from the opposition also campaigned against each other throughout most of 2021 and only showed a united front after the primaries in the autumn of 2021.

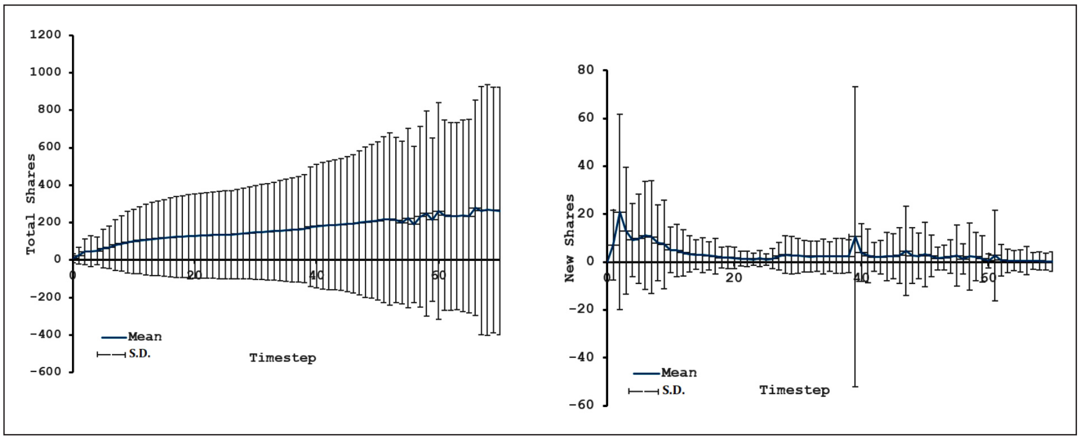
[1] https://kozvelemenykutatok.hu/2020-januari-kutatasi-eredmenyek-idea/

Crowdtangle data does not include any information about the private accounts that interact with certain posts; however, basic information is available about the Facebook page that created the post, such as the number of likes, number of followers, and country of posting. Thus, this information is available for every party and party leader's page. Crowdtangle data can be used in two ways: in the form of a summary of posts from a certain period from certain users or a detailed summary of all posts. In our analysis, we use both.

Throughout the period, 146 posts were collected from the 16 Facebook pages of the Hungarian party leaders. The collected data contains the number of reactions of each type ('like,' 'love,' 'care,' 'haha,' 'angry,' and 'sad') to posts from the parties and their leaders. The appendix contains the details of the posts published by these political actors.

Statistical analysis

A **B**



C

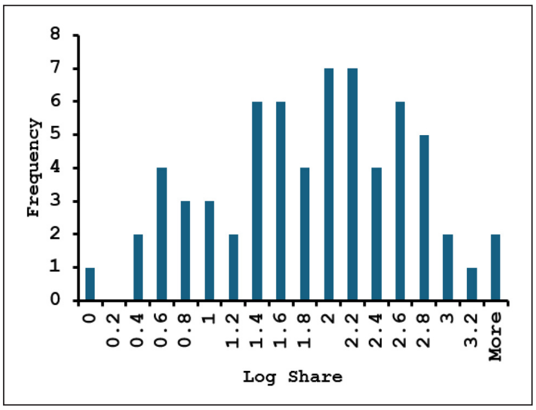


Figure 1 A-B: Means and standard deviations of the total shares (A) and new shares (B) of posts in different time steps. C: Distribution of log(shares) after 70 time steps (16 days). Note: Crowdtangle time steps are not linear; steps 1-5 represent 15 minutes; steps 6-26, 30 minutes; steps 27-38, 1 hour; steps 39-46, 3 hours; steps 47-54, 6 hours; 55-60, 12 hours, and 61-70, 1 day.

The distribution of sharing behavior indicates that it is rather skewed; the median post was only shared 77 times. However, some successful posts were shared more than a thousand times. Therefore, we plotted the logarithm of total shares (Figure 1 C). Regarding sharing over time (Fig 1B), there is a rapid take-off period in sharing in the first two steps and then a gradual decrease. (The 'bumps' in Fig 1 A-B correspond to changes in the length of the time period represented in specific time steps, e.g., time represented by a time step doubles after step 5 and step 26).

After considering the distributions, we created a regression model to analyze sharing dynamics. Thus, New Shares for each post within a specific time step will be our dependent variable.

The New Shares variable is a discrete count variable for which research usually applies count regressions, most frequently Poisson or negative binomial regression. Negative binomial regression is a statistical method that is suitable for analyzing over-dispersed count data where the conditional variance exceeds the conditional mean. This condition is true for the New Shares variable, as Table 1 shows.

Table 1 Description of New Shares variable

	Mean	**SD**
New Shares (N=9514)	3.3	13.7

As independent variables, we use Comments and Reactions over time to differentiate between overall user engagement and emotional reactions. In particular, we predict the quantity of New Shares with the quantity of New Reactions and New Comments in the previous Timestep. Additionally, the Time Period variable was added as an independent variable to the model to control for possible decreasing engagement over time, as we observe in Fig 1B. Furthermore, as we observe that engagement with specific posts is highly variable, we added post-specific fixed effects to the model to capture the differences in the attractiveness of the post. Correspondingly, we estimate the following regression

$$log\ (NewShare_{i,t}) = \beta_0 + \beta_1\ NewReactions_{i,t-1} + \beta_2\ NewComments_{i,t-1} + \beta_3\ t_i + \xi_i \qquad (1)$$

Where *t* represents the specific Timestep, *i* is the indicator of the post, and ξ_i stands for the post-specific fixed effect.

Table 2 presents the results of the regression analysis corresponding to Equation 1. The findings indicate that the New Reactions variable has a significant positive effect on the number of New Shares, suggesting that reactions and shares are associated, even after controlling for the quality of the post according to fixed effects. Thus, positive feedback between these variables may be present in the social network. Comments, however, were not associated with such an effect. Time, furthermore, has a negative impact on new shares, even after controlling for the previous engagement. Because the possibility of multicollinearity of these variables arises, we tested for this. VIF values for the explanatory variables were in the moderate range (2.23, 2.25, and 1.02 for New Reactions, New Shares, and Time, respectively). This regression framework corresponds to the decreasing engagement that we observed in Fig 1A-B. This phenomenon in the diffusion models comes from the saturation effect – the impact of the decreasing pool of agents susceptible to a new product or disease.

Table 2 Regression analyses of New Shares by lagged Reactions, Comments, and Time Period

	New Shares
New Reactions (t-1)	0.006***
New Comments (t-1)	0.00
Time Period	−0.96***
Observations	9,329

Note: *p<0.1; **p<0.05; ***p<0.01.

Agent-based model

In our agent-based model, we aim to analyze the diffusion of political news under different conditions with regard to network structure, homophily and echo-chamber effect, and the presence of a preference-based filtering algorithm. Building on diffusion models and our previous empirical analysis concerning the dynamics of sharing political news on Facebook, the simulation aims to create a simplified model of news sharing. Our observation is that reactions propagate future shares, and we incorporate them into the model by adding reactions as a separate channel, which increases the visibility of posts to friends. We consider the fixed effect term in the regression analysis to be the attractiveness of the post in the simulation. Corresponding to previous studies and because online social networks have been shown to exhibit properties predicted by different network models, three different network structures are simulated: random, small world, and preferential attachment. We consider these with or without homophily and with or without filtering algorithms to compare information-sharing under various network environments.

Considering the network structure, we have seen that the network structure of online social networks combines several features of basic models. Therefore, we follow the earlier literature and consider three network models for the simulation, being aware that none of these fully characterize real social networks. Under the random network condition, links between agents are formed probabilistically between nodes with uniform probability. Small world refers to a network that has high clustering (friends of friends tend to be friends) and relatively low average distances between nodes. High clustering is achieved by distributing the nodes on a circle and creating connections between each of them within a certain range on the circle. As the resulting network has high distances, in the next step, a small fraction of links are redistributed randomly to create 'shortcuts.' In preferential attachment networks, connections are distributed according to how many connections the node already has.

Echo chambers refer to the phenomenon of groups of like-minded users forming on social media and where there is a bias in the information diffusion toward like-minded users (Quattrociocchi et al., 2021). The homophily of users is one mechanism behind echo chambers, but social media algorithms may reinforce the effect (Cinus et al., 2022). Homophily refers to the tendency for connections to occur at a higher rate amongst those who share a common interest (McPherson et al., 2001).

In the simulation, homophily is operationalized as a higher number of links being simulated between those whose political interests are similar under the homophily condition. With respect to algorithms, a content-filtering algorithm was considered, whereby posts are shown with decreased probability to those users whose political attitude is more distant from the sender. To examine the potential interactions, each of the three types of network structures was simulated with and without homophily and with or without a preference-based filtering algorithm. The simulation was implemented using the Netlogo software package.

The news sharing in the simulation was implemented the following way. Each agent represents a person, a member of a social network. A fraction of agents are selected to be 'followers' of the politician; they are shown the information in the first timestep. Their neighbors are the connected nodes who can see their activities –reactions or shared posts. The number of neighbors of a given agent – the node degree – depends on the network structure. The sender (politician) is modeled as being external to the network. Political attributes are assumed to be one-dimensional: the politician stands at the zero point, and the agents are at different distances from it, modeled by a uniformly distributed 'interest' parameter. The politician posts different information having a random attractiveness parameter and political specificity. Sharing happens randomly based on the attractiveness of the post, its political specificity, and the distance between the agent and the politician on the political spectrum. (Specifically, the attractiveness parameter decreased by the political distance between the politician and the agent and by the political specificity of the post, which is evaluated against a random number). Reacting to the post happens similarly to sharing but with a higher probability.

Non-follower agents – agents that did not see the information in the first timestep – are only shown the post if their neighbor shared it or reacted to it. This, however, is not automatic. Posts shared (or reacted to) by friends are made visible to users randomly based on their political attitudes. Specifically, their distance from the politician decreased by the political specificity of the post is evaluated versus a threshold. We manipulate the content-filtering algorithm using this threshold. In the baseline case, almost everyone can see the post, while in the 'filtering algorithm' scenario, only those whose attitude is close to that of the politician can see it.

Thus, the simulation consists of the following steps:

1. A [Random / Preferential Attachment / Small Word] network of people is created, having different attitudes ('interest') towards the sender [with / without] homophily. Some people are selected to be followers of the sender. The attractiveness of the post is defined.
2. Followers are set as eligible to see the post.

3. The post is shown to those who are eligible to see it and have attitudes close enough to the sender. In the filtering algorithm scenario, a strict threshold is applied; without the filtering algorithm, this threshold is loose.
3. Those who have seen the post and have not shared it yet decide if they will share it based on their attitude towards the post and the attractiveness of the post.
4. Those who have seen the post and have not reacted yet decide if they will react to it based on their attitude towards the post and the attractiveness of the post.
6. The connections of those who have shared the post or reacted to it are set as eligible to see the post.
7. The cycle starts over from Step 2.

In our baseline simulation, the network consists of 400 nodes, of whom 20 are followers of the politician, and 380 are not. Each node has an average degree of 4. Additionally, the simulation was repeated with different settings to test the robustness of the results. Table 3 summarizes the different settings for the simulation. The number of nodes and average node degree were modified, and in the case of small-world networks, the probability of the rewiring of the network was tested using two versions.

Table 3 Settings for the agent-based simulations

Scenario	**Network Type**	**Number of Nodes**	**Average Node Degree**	**Number of Followers**
A	Small world (p = 0.1)	400	4	20
	Preferential Attachment	400	4	20
	Random	400	4	20
B	Small world (p = 0.1)	1000	4	50
	Preferential Attachment	1000	4	50
	Random	1000	4	50
C	Small world (p = 0.1)	1000	10	50
	Preferential Attachment	1000	10	50
	Random	1000	10	50
D	Small world (p = 0.05)	400	4	20

In Scenario B, we increased the network size from 400 to 1000 nodes, holding the average node degree constant. The number of followers was also increased proportionally to maintain the same ratio as before. In Scenario C, the number of nodes and the node degree were also increased by a factor of 2.5 compared to the original setup, resulting in a similar network density but a higher average degree. Last, Scenario D specifically targets small-world networks, testing a modification to the rewiring probability.

4 Results of the simulation model

4.1 Baseline specification

Table 4 presents the results of the baseline version of the ABM. The number of agents who have shared, watched, and reacted to the post in the 100th step of the simulation is presented. Results show that with each network type, a filtering algorithm decreases the number of agents who interact with the post and its final reach. Additionally, homophily tends to increase interaction with the post if a filtering algorithm is present. Results indicate that the highest average count of individuals who viewed, reacted to, or shared a post occurred within small-world networks, particularly those without filtering algorithms and incorporating homophily. On the contrary, the lowest count of nodes engaging in sharing was observed in random and preferential attachment networks, particularly those without homophily and with the presence of a filtering algorithm.

Table 4 Average number of agents at each step who watched/reacted to/shared the post in the 100th step of 100-iteration Scenario A

Network Type	Homophily	Filtering algorithm	Number of nodes	Average node degree	Number of followers	Watched	Reacted	Shared
Small world	false	false	400	4	20	215.5	139.3	122.4
Small world	false	true	400	4	20	133.1	59.9	50.6
Small world	true	false	400	4	20	205.9	152.4	130.8
Small world	true	true	400	4	20	132.6	84.4	70.8
Random	false	false	400	4	20	180.2	103.5	74.2
Random	false	true	400	4	20	95.7	37.8	25.7
Random	true	false	400	4	20	160.5	105.9	75.3
Random	true	true	400	4	20	100.7	47.0	32.1
PA	false	false	400	4	20	156.4	77.4	57.0
PA	false	true	400	4	20	88.2	36.3	26.1
PA	true	false	400	4	20	163.0	99.4	71.7
PA	true	true	400	4	20	92.6	43.3	29.2

In Figure 2, we focus on sharing and visualizing the dynamics of Total Shares under these conditions. First, it is reassuring that the general shape of the diffusion curves is similar to what we observed in Figure 1A about the sharing of political content on Facebook. We can also visually observe what we have seen from Table 4 – that small-world networks without filtering are the ones with the most efficient spreading, and homophily, in general, supports spreading. However, its effects are highly variable across the specifications.

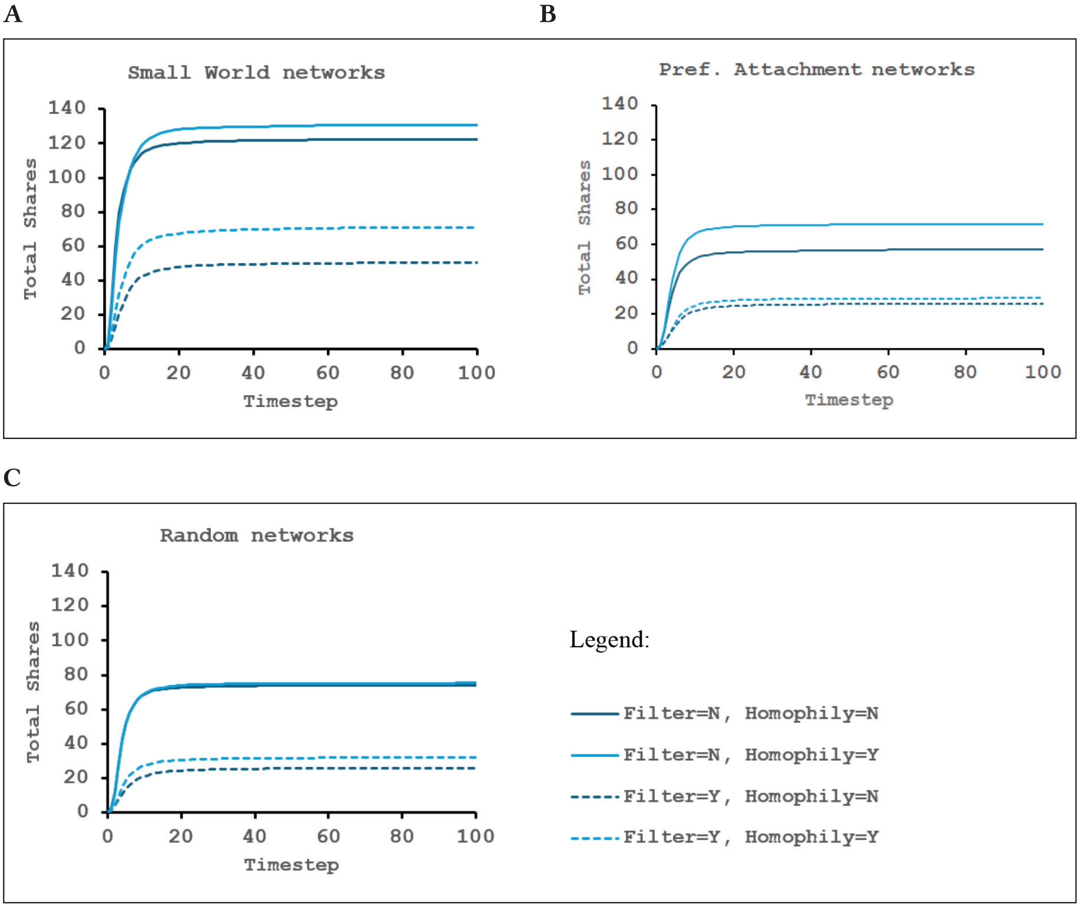


Figure 2 Average number of shares over the 100 steps of the simulations in different networks: **A**. Small World networks **B**. Preferential Attachment networks C. Random networks. -

To test the statistical significance of the influence of the different network attributes, a linear regression was applied to the number of nodes that shared the information in the simulation. The number of agents that shared the original information was explained by the network type, homophily, the presence of filtering algorithms, and the pairwise interactions of these factors. Accordingly, the following equation was estimated:

$$\begin{gathered} TotalShare = b_0 + b_1\, SmallWorld + b_2\, PA + b_3\, Random + b_4\, Homophily + b_5\, FilterAlgorithm + \\ b_6\, Homophily \times FilterAlgorithm + b_7\, PA \times Homophily + b_8\, Random \times Homophily + \\ b_9\, SmallWorld \times Homophily + b_{10}\, PA \times FilterAlgorithm + b_{11}\, SmallWorld \times FilterAlgorithm + \\ b_{12}\, Random \times FilterAlgorithm + \varepsilon \end{gathered} \tag{2}$$

Regarding network type, the coefficients of small world and preferential attachment (PA) networks were measured, and random networks served as a reference category, as the linear regression contained the network types as dummy independent variables.

Table 5 Linear regression analysis of network attributes' influence on the total number of agents sharing posts in simulation Scenario A

	B
Intercept	181.82***
Small World	−16.81
Preferential Attachment	−54.21*
Homophily	−29.99
Echo chamber	−90.93***
Homophily and Echo chamber	26.77*
Homophily in Preferential Attachment	12.61
Homophily in Small World	19.38
Echo Chamber in Preferential Attachment	17.8
Echo Chamber in Small World	14.69
Adjusted R2	0.07943
Multiple R2	0.08634
Observations	1200

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 5 shows the estimation results corresponding to Equation 2. It shows that after one hundred timesteps, significantly fewer agents share the information in preferential attachment networks than in random networks, corresponding to the earlier descriptive finding. However, the regression analysis does not find that news spreads significantly more rapidly the small world network than in the random ones. Although both homophily and filtering algorithms may be viewed as mechanisms that restrict diffusion, homophily did not cause a statistically significant decrease in shares on its own. (In fact, in the descriptive statistics, it seemed to have a positive impact instead). The filtering algorithm was shown to have a negative impact on the regression analysis, similar to the descriptive results. Further, the regression model shows that the presence of homophily counteracts the negative effect of filtering algorithms; if both were introduced in the networks, this resulted in more total shares.

Alternative specifications

Table 6 displays the result of the simulations run over a bigger network but with the same average degree. From the average statistics, we can observe that, in general, the news spreads more or less similarly in the three network types if there is no filtering algorithm. With filtering algorithms, however, small-world networks seem to perform somewhat better. Further, homophily supports spreading in cases when the filtering algorithm is present (in all network types), but when it is not present, its impact depends on the network type.

Table 6 Average number of agents at each step who watched/reacted to/shared the post in the 100th step of 100-iteration Scenario B

Network Type	Homophily	Filtering algorithm	Number of nodes	Average node degree	Number of followers	Watched	Reacted	Shared
Small world	false	false	1000	4	50	558.0	295.2	268.5
Small world	false	true	1000	4	50	466.4	216.8	191.7
Small world	true	false	1000	4	50	555.4	407.0	365.5
Small world	true	true	1000	4	50	443.3	308.6	273.8
Random	false	false	1000	4	50	524.0	345.9	282.9
Random	false	true	1000	4	50	331.2	149.5	115.9
Random	true	false	1000	4	50	595.4	441.3	353.6
Random	true	true	1000	4	50	386.4	246.9	192.2
PA	false	false	1000	4	50	537.1	318.7	264.9
PA	false	true	1000	4	50	334.1	150.2	118.8
PA	true	false	1000	4	50	517.1	354.8	289.2
PA	true	true	1000	4	50	321.3	193.2	151.5

The results of the simulations corresponding to Scenario C, a network similarly large to Scenario B but with higher density, are presented in Table 7. Compared to the previous scenario, we see that the higher density somewhat increased the number of shares in the small-world network but not in the other two types. This results in small-world networks seeming to outperform the other two networks in each scenario. In this setting, the Total Shares after 100 steps were, on average, higher in each scenario that included homophily, compared to the similar setting without homophily.

Table 7 Average number of agents at each step who watched/reacted to/shared the post in the 100th step of 100-iteration Scenario C

Network Type	Homophily	Filtering algorithm	Number of nodes	Average node degree	Number of followers	Watched	Reacted	Shared
Small world	false	false	1000	10	50	703.8	410.9	364.9
Small world	false	true	1000	10	50	472.6	232.2	200.2
Small world	true	false	1000	10	50	563.5	466.8	416.7
Small world	true	true	1000	10	50	501.7	393.1	344.4
Random	false	false	1000	10	50	612.3	358.3	265.1
Random	false	true	1000	10	50	470.6	199.3	134.7
Random	true	false	1000	10	50	478.8	331.9	232.5
Random	true	true	1000	10	50	392.6	285.0	199.6
PA	false	false	1000	10	50	549.3	299.7	224.4
PA	false	true	1000	10	50	415.0	180.8	126.6
PA	true	false	1000	10	50	562.0	386.1	286.2
PA	true	true	1000	10	50	362.5	237.0	164.8

Regarding the small world network, the simulations with the increased rewiring probability, that is, with more 'distant' ties but on the same network size as our baseline (Scenario A), are presented in Table 8. The number of shares at the end of the simulation somewhat increased in the new version compared to the original one (Table 4) when a new filtering algorithm is applied, but no change can be observed when filtering limits the visibility of posts. Similarly to the original scenario, homophily tends to mitigate the limiting effect of the filtering algorithm.

Table 8 Average number of agents at each step who watched/reacted to/shared the post in the 100th step of 100-iteration Scenario D

Network Type	Homophily	Filtering algorithm	Number of nodes	Average node degree	Number of followers	Watched	Reacted	Shared
Small world	false	false	400	4	20	242.1	148.7	129.3
Small world	false	true	400	4	20	139.5	62.6	52.8
Small world	true	false	400	4	20	197.6	150.7	130.1
Small world	true	true	400	4	20	183.0	115.9	96.0

Comparing the different scenarios, the following tendencies can be observed. First, it is visible that the filtering algorithm limits the spread of news in the network, which is not surprising given that this mechanism directly limits the visibility of the post to users having different political preferences from the sender. Second, small-world networks seem to have an advantage in spreading the news. However, this is not consistent across different network structures and sizes in general. What seems consistent is that these networks perform better if there is a filtering algorithm. Third, homophily tends to act as a facilitator of diffusion in contrast to a limiting factor. This tendency is also not consistent across all network structures and sizes, but it is present in all specifications when the filtering algorithm is present.

After observing these tendencies, we should also check if the above differences are systematically present and statistically significant over the simulation runs. To do this, we re-run the linear regressions corresponding to Equation 2 on the alternative specifications.

The results of the regressions are summarized in Table 9. Columns B – D represent the corresponding alternative specification, while we included the results of the baseline specification again in column A for a clearer overview. The regression analysis only partly supports the descriptive tendencies described above. The tendency that, in the case of filtering algorithms, small world networks are more efficient in terms of spreading the news (as compared to random networks) is supported in scenarios A and B but not in the bigger, denser network (Scenario C). The tendency for homophily to counteract the negative impact of the echo chamber is supported in the original scenario and also in the small world network with more distant ties (Scenario D), but not in the bigger network (Scenario B), while in the case of Scenario C, the positive effect of homophily is specific to small-world networks.

Table 9 Linear regression analysis of the influence of network attributes on the total number of agents sharing posts in Scenarios A, B, C, and D

Scenario	**A**	**B**	**C**	**D**
Intercept	181.82*** (33.72)	371.5*** (103.35)	430.85*** (101.76)	247.75*** (61.36)
Small World	−16.81 (30.65)	−105.2075 (93.93)	56.28 (92.48)	
Preferential Attachment	−54.21* (30.65)	4.07 (93.93)	−16.14 (92.48)	
Homophily	−29.99 (19.89)	73.995 (60.95)	−66.94 (60.01)	−41.82 (38.81)
Echo chamber	−90.93*** (19.89)	−163.725** (60.95)	−164.81** (60.01)	−119.14** (38.81)
Homophily and Echo chamber	26.77* (11.48)	−0.3233 (35.19)	55.44 (34.65)	42.55* (24.54)
Homophily in Preferential Attachment	12.61 (14.06)	−45.06 (43.09)	33.76 (42.44)	
Homophily in Small World	19.38 (14.06)	16.035 (43.09)	81.75* (42.44)	
Echo Chamber in Preferential Attachment	17.8 (14.06)	22.31 (43.09)	−27.98 (42.44)	
Echo Chamber in Small World	14.69 (14.06)	79.925* (43.09)	−36.89 (42.44)	
Multiple R2	0.07943	0.05882	0.0711	0.05571
Observations	1200	1200	1200	400

Note: *p < 0.05; **p < 0.01; ***p < 0.001

5 Discussion

Online politics influence offline political action through social media. Research has shown that offline mobilization in online spaces is most effective through the sharing of political content with people we know. In this article, we sought to explore the logic of news sharing on social media.

Our aim was to examine the impact of factors that previous research has shown to influence sharing: network structure, homophily and echo chambers, and filtering algorithms. To base our agent-based model, we analyzed Facebook posts of Hungarian politicians from 2021. However, beyond the fact that Facebook dominated the social media landscape, the field of study is not specific. In the social media environment, information diffusion is influenced by an algorithm that is linked to friends' interactions with the information (Bucher, 2012). Interactions regarding a post on Facebook can involve expressing emotions via reaction buttons, commenting, and sharing. The focus of the analysis is sharing. This was explained by other reactions in the regression model, and it showed a significant effect on the number of shares. Thus, it was implanted into an agent-based model.

Because online social networks share various characteristics of network models, corresponding to the literature, three network models — small world, preferential attachment, and random networks — were compared. The simulation confirmed the importance of weak ties in social networks; most people were reached by shared news in small-world network scenarios, corresponding to the findings of prior research (Centola, 2010; Pegoretti et al., 2012). A novel element in the analysis is, however, that small-world networks overperformed preferential attachment (Albert & Barabási, 2002) networks, too, in terms of the final reach of information. When comparing the different network scenarios, it was observed when network density was relatively low and/or the spread of the news was constrained by a filtering algorithm.

This result may be due to two features of the model. First, sharing is not automatic; it depends on the political alignment of users, who are heterogeneous in this regard. Second, there is no social influence in our model. Therefore, if a central person is very negative towards a politician, they will not share the information, even if many of their friends do. Thus, high centralization in our model may stop the diffusion process if the central person happens to be skeptical, while in a less centralized network, like in a random or small-world network or the case of denser preferential attachment networks, the information bypasses the skeptical person more easily.

The feature of the heterogeneous thresholds of the agents is typical in diffusion models. Otherwise, the diffusion question would be reduced to the question of the shortest path in the network. The lack of social influence is not that typical; such a mechanism is included in several related models. In opinion dynamics models, e.g., Baumann et al. (2020), the basic assumption is that neighbors in networks influence each other. In network models of collective action, like a protest, for example (Chwe, 1999; Korkmaz et al., 2019), individuals favor acting only if enough others act similarly. This setup is similar to the adoption of innovations if the innovation includes a network externality because its utility comes from connecting people, like a messaging system (Aral et al., 2013). The lack of a social influence mechanism in our model also means that the advantage of small-world networks associated with locally dense structures (high transitivity) that ensure collective action and network-based diffusion (Pegoretti et al., 2012) is not present in our model.

The emergence of echo chambers has been at the forefront of social media research recently (Del Vicario et al., 2016; Quattrociocchi et al., 2021), which this article approaches by introducing homophily to the networks together with a bias in the social media algorithm that filters content according to its fit with the attitudes of the agents. In general, we find that the impact of homophily varies across networks depending on the structure and specification, similar to Korkmaz et al. (2019). An interesting result of our simulation is that in the cases when the diffusion of news is limited by a content-filtering algorithm, homophily enhanced diffusion of the news, especially in small-world networks, instead of limiting it. This result contrasts with what we had expected based on earlier studies arguing that homophily and computer algorithms amplify each other in creating echo chambers (B. Jiang et al., 2021) and showing that diverse connections boost diffusion (Cota et al., 2019). About this result, it can be argued that in the case of bounded diffusion opportunities, when the news itself is not very attractive, and the filtering algorithm does not allow it to be seen by politically distant agents, homophily does not act as a limiting factor, but as an enhancing factor of diffusion. This happens because the connections between similar people create a path through which the politically interested agents can be reached by the news. In this setting, without homophily, the spread of the news stops early, and agents who are politically interested but distant in the network from the source are not reached. Results show that homophily has a positive effect when echo chambers are present, especially in network types where diffusion is low on average, supporting this interpretation. Thus, in other words, echo chambers have the function of enhancing diffusion in the case of news that has a more limited potential audience. Note that we find this without taking into account the attention constraints of users, under which condition filter bubbles have the additional function of creating a stream of potentially attractive content that users are willing to share.

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Appendix

Name	Number of posts	Number of Followers at Posting	Number of Likes at Posting	Total Likes	Total Com-ments	Total Shares	Total Love	Total Wow	Total Haha	Total Sad	Total Angry	Total Care	Total Inter-actions
Demokratikus Koalíció	8	1317882	1177101	9210	581	1645	132	52	57	250	166	108	12201
Dr. Tóth Bertalan	2	70804	67440	8222	599	4428	50	116	213	697	990	53	15368
Fekete-Győr András	5	200855	186283	4413	2219	628	85	43	544	100	299	29	8360
Fidesz	28	8923704	8867640	38805	1465	5200	273	46	225	168	341	377	46900
Gyurcsány Ferenc	2	578164	534622	3130	1191	839	343	6	111	15	42	148	5825
Jakab Péter	5	1182516	944805	13526	1692	1862	164	35	129	510	1033	145	19096
Jobbik Magyarországért Mozgalom	15	7798134	7729951	12335	3913	7807	75	389	4250	950	5431	49	35199
Kanász-Nagy Máté	6	31329	30612	227	35	65	1	5	7	7	4	3	354
Karácsony Gergely	7	1892085	1822456	39745	4112	4357	2078	584	995	105	287	1227	53490
Kunhalmi Ágnes	2	84397	82318	1164	252	30	77	0	4	0	0	169	1696
LMP – Magyarország Zöld Pártja	10	740252	763466	209	38	69	4	5	10	5	24	1	365
Magyar Szocialista Párt	17	3668436	3541908	9937	694	3342	125	28	50	179	400	153	14908
Momentum Mozgalom	14	1621291	1512826	3894	437	301	143	28	163	30	147	66	5209
Orbán Viktor	4	4435914	3620652	32417	5178	741	632	57	1324	20	295	439	41103
Párbeszéd Magyarországért	14	1835916	1776396	7224	1363	1761	22	74	446	1768	2030	63	14751
Schmuck Erzsébet	7	223583	242210	311	27	35	1	3	2	3	13	2	397
Szabó Tímea	0	-	-	0	0	0	0	0	0	0	0	0	0
Total	146	34605262	32900686	184769	23796	33110	4205	1471	8530	4807	11502	3032	275222

Appendix 1 Summary of Facebook posts collected (Source: Crowdtangle)