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BOM IN SOCIAL NETWORKS

How exposure to different opinions impacts the life cycle of social media

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Abstract As a lot of communication and media consumption moves online, people may be exposed to a wider population and more diverse opinions. However, individuals may act differently when faced with opinions far removed from their own. Moreover, changes in the frequency of visits, posting, and other forms of expression could lead to narrowing of the opinions that each person observes, as well as changes in the customer base for online platforms. Despite increasing research on the rise and fall of online social media outlets, user activity in response to exposure to others' opinions has received little attention. In this study, we first introduce a method that maps opinions of individuals and their generated content on a multi-dimensional space by factorizing an individual–object interaction (e.g., user-news rating) matrix. Using data on 6151 users interacting with 287,327 pieces of content over 21 months on a social media platform we estimate changes in individuals' activities in response to interaction with content expressing a variety of opinions. We find that individuals increase their online activities when interacting with content close to their own opinions, and interacting with extreme opinions may decrease their activities. Finally, developing an agent-based simulation model, we study the effect of the estimated mechanisms on the future success of a simulated platform.

Keywords Social media · User activity · Opinion measuring · Agent-based simulation

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1 Introduction

Social media platforms have become an important part of our daily lives. Social networks such as Facebook and Twitter, messaging applications such as WhatsApp and Viber, and picture and video sharing platforms such as Instagram and Snapchat have a big influence on our daily lives. For example, more than a third of 18 to 29-year-old Americans identified social media as their most helpful resource for learning about the 2016 presidential election (35% social media, 18% news websites and applications, and 12% cable TV news) (Gottfried et al. 2016). And this trend is increasingly global: Facebook, with more than 1.86 billion monthly active users, has grown more populous than China; Add to that the more than one billion active users of YouTube, 600 millions of Instagram, 319 million of Twitter, and 106 million of LinkedIn, and the global reach of social media outlets becomes even clearer. This is a dynamic marketplace where most big companies of today grew from obscurity, defeating other major social media platforms just a few years ago: Facebook defeated Myspace, and YouTube replaced shareyourworld.com. Similar examples of boom and bust in online social media are common over the past decade.

Researchers have studied various aspects and causes of these cycles. In one study, Cannarella and Spechler (2014) developed an SIR (susceptible, infected, and recovered) model for explaining trends of user activity on Myspace and predicted that Facebook would lose 80% of its peak users by 2017 and its users would migrate to other social network outlets. Torkjazi et al. (2009) studied the activities of Myspace users and discussed the various factors behind user departure from social networks. They built on the idea that social networks are vulnerable to new fads; therefore, it is important to innovate and add new features to platforms in order to keep users interested. They also discussed the importance of linking users to other like-minded individuals when the platform grows. Wu et al. (2013) studied the relationship between user arrival and departure on social networks with respect to network topology, and elaborated on the important role of active friends in social networks in departure decisions. In another study based on network topology, Garcia et al. (2013) focused on understanding the resilience of social networks and how friends' departures impact focal users. Giliette (2011) provided a more popular view on some of the technical, managerial, financial, and social issues that could lead to social media outlet failure. Among relevant factors, he highlights lack of technology (e.g., spam filtering in the case of Myspace), poor choice of advertising services (e.g., inappropriate advertisements in Myspace), and bad publicity (e.g., a court case about inappropriate content for children on Myspace).

Information privacy is another research area which, if not attended to, may contribute to the loss of users. Individuals' trust may affect their activity level on social media. For example, Facebook users expressed greater trust in the platform than MySpace, which increased their willing to share their information (Dwyer et al. 2007). However, the user's willingness to act to preserve their privacy has not been well established. Madejski et al. (2011) identified a mismatch between sharing intentions of users on Facebook and their privacy settings, an issue that has also been identified for the users on blogging platforms (Viégas 2005).

Innovation and specialization is also another potential driver of changes in social media landscape. New social media platforms target specific interactions (e.g., dating applications and professional social networks), and the conventional use of social media is changing, which may affect user activity and engagement and the competitive landscape (Lampe et al. 2008). For instance, photo sharing social networks such as Pinterest and Instagram attracted significantly more users than Facebook during 2014 and 2015 (Greenwood et al. 2016).

On the user side, individuals may be learning about what social media can do for them and their needs may be changing too. For example, the sense of connectivity and entertainment are among the major benefits users identify for social media (Boyd 2007). However, heavy use can reduce bonding and increase loneliness (Burke et al. 2010). Besides connecting to similar people, i.e., bonding, Ellison et al. (2007) identified the important bridging role of social media (i.e., social ties linking diverse people). Usage also varies based on individuals' degree of self-esteem and satisfaction with life. Those lower on this scale may find social media more useful as it offers non-traditional options for connecting with others (Ellison et al. 2007). Research has shown that increased frequency of updating Facebook status helps reduce loneliness (Deters and Mehl 2013), and anonymity (on certain platforms) or lack of face-to-face online communication can decrease self-consciousness and social anxiety (Morahan-Martin and Schumacher 2003). To the extent that these benefits change over time, or users learn about them, the use cases for social media and the appeal of different platforms would change.

Besides the factors highlighted above, the rise and fall of a platform depends on individuals engaging with or leaving the platform—their actions depends on how much they enjoy their interactions within the platform. Some of those interactions have been studied under social influence research. From making a simple estimation (e.g., Jalali 2014) to more major decision-making processes (e.g., Tanford and Montgomery 2015), individuals' opinions are influenced by others. On rating-based social news platforms in particular, research has shown that social influence substantially biases rating dynamics; prior ratings of news can have a significant effect on individual rating behavior (Muchnik et al. 2013). Social influence is a very strong finding that applies across most individuals, even though individual variations exist, e.g., internal political self-efficacy moderates social influence on political topics (Lee 2014). Such social influence patterns can homogenize behavior. For example, Kim and Lee (2014) showed that highly active users on Twitter tend to show consistent behavior patterns by retweeting others who have the same viewpoints. An et al. (2014) summarized four theoretical motivations in sharing political news: selective exposure (sharing news that one likes and agrees with); trust and intimacy (based on credibility of the news source); gratification (enjoyment or informativeness of the news); and socialization (sharing news matching the leanings of the user's followers). While the extant literature has analyzed the impact of social influence on liking and sharing a piece of content, the other side of the coin remains less studied. Specifically, we do not know much about the impact of the actual opinions *consumed* on the activity patterns of social media users. Social media platforms allow ordinary users to generate content and consume content provided by others. In such an environment, user-generated content is the fundamental building block of the platform. This creates a path dependent and endogenous feedback system in which the history of past activities and content has a major effect on the actions of users in the future and the content that will be generated. To fully understand this system, we need both an understanding of what content gets shared and promoted, and what the consumption of that content does to the future activity patterns of users. The focus of the current study is to better understand this complex system, by first analyzing the impact of various content consumption patterns on user activity, and then simulating how those reactions add up to shape the evolution of a social media platform.

Teasing out the endogenous drivers of user contributions in a multi-faceted social media is complicated: people may post personal pictures, political articles, short stories, and their current emotions for different reasons. Therefore, we focus on addressing this question in a particular type of platform, one that focuses on sharing and rating news, i.e., social news websites. On social news websites, users produce content (i.e., share news) based on their own viewpoints and opinions on a variety of topics. The content generated by some users may

be repulsive from the perspective of others, which could affect their behaviors and activities in the social media, offering an appealing empirical setting to analyze our research question.

In this study, we contribute to a better understanding of how content and user activity coevolve, a complex process that partly explains the growth and failure of social network platforms and their content composition. To this end we used opinion data extracted using a novel opinion mapping method introduced in Ashouri Rad (2016), and estimated regression models to study changes in individual activities (i.e., posting, commenting, and revisiting rates) influenced by interacting with a variety of opinions. Extracting the mechanisms affecting online communities, we simulated and predicted the future formation of the communities. We also studied the effects of community bias and extremeness on its evolution. Finally, based on our simulation analysis, we proposed different interventions that can help increase user activity and the life cycle of social media outlets. Studying user activities and behavior can help us understand the social behaviors of communities in general and individuals in particular. It can also assist social media outlets in design, decision-making and policymaking.

The rest of this paper is organized as follows. In Sect. 2, we present the data and case study. Our methodology is presented in Sect. 3, where we first discuss our analytical models (Sect. 3.1) and then our simulation model (Sect. 3.2). The results of these two approaches are presented in Sects. 4.1 and 4.2, respectively. Section 5 discusses the findings.

2 Data and case study

We used data from one of the first and largest Persian social media platforms, a social news website (similar to Digg and Reddit) which has gathered over 60,000 registered members, 2.5 million stories, 65 million votes, and several million comments since its inception in August 2006 until the beginning of 2016 for which we had data. We selected this social media platform because: (1) The sole focus of the platform on story sharing facilitates analyzing the effect of users' behavior on the dynamics of the growth of social media, with no need to tease out that effect of other influences; (2) We could secure full access to its data; and (3) The mechanisms of the platform are similar to those of other story-sharing platforms in other languages, which help increase the generalizability of our findings.

Because our case study platform is based outside Iran, it is not restricted by the Iranian government's regulations. Hence, it quickly became an environment in which users could freely discuss politics, particularly the Iranian government and its policies. After the presidential election in 2009, the platform was used as one of the channels for coordinating protests to the government. Consequently, a large portion of its content is concentrated on Iran's government and its political issues, which we focus on in our analysis. We collected data from August 2006 to May 2008 on all active users and stories (users who cast votes and stories that received votes). This provided us with behavior data on 6151 active users who posted multiple stories (and thus their activity over time could be tracked) and properties of 287,327 stories with multiple votes.

Users can post stories (links containing news, videos, pictures, etc.—we consider them all as online objects) as well as comments. They can also vote for other stories. Stories published recently are viewed on an ordering page (called a recently published stories ordering page) in which stories are sorted in chronological order. The life cycle of the stories on this page is one day, after which stories are moved to an archive page. Once users initiate posts, they can select a related category (political, social, sport, etc.), but we specifically focus on political

content and limit our analysis to that, because: (1) political content forms the majority of posted items; (2) polarity and segregation of opinions are more salient for political content.

3 Methodology

We first present our analytical modeling (Sect. 3.1) in two sub-sections, *opinion estimation methodology* (3.1.1) and *regression analysis* (3.1.2). We then present an agent-based simulation model (Sect. 3.2). The results are discussed in Sect. 4. Further results, along with more information about our analysis which facilitates further analysis and development are documented in the Online Supplementary Materials.

3.1 Analytical models

For the analytical modeling, we first estimated the opinions of individuals and of the objects on social media using a novel opinion estimation method. The basic idea is that we can define an opinion space with multiple dimensions and locate each individual and each online object on that space. For example, a potential dimension of an opinion space on our platform may include orientation towards the Iranian government (i.e., supporting or opposing). This could be a continuous metric with positive values for support and negative values for opposing individuals or objects. We let the actual dimensions emerge from our estimation algorithm, so that every individual and story is located on the same two-dimensional space consistent with the patterns of voting that suggests which individual holds opinions close to those embedded in which objects.

Then, based on the estimated opinion of each individual and the estimated opinion expressed by the content they are exposed to, we studied the effect of interacting with various opinions on individual online activity. Therefore, our analytical modeling analysis is divided into two sections: (1) *Opinion estimation method*, which maps out the opinions of individuals and their generated content in a multi-dimensional space by factorizing an individual–content rating matrix into opinion matrices for individuals and content; (2) *Regression analysis*, in which we propose three regression models (one for each type of activity under study: posting, commenting, and revisiting) to analyze the effect of interacting with various opinions on individual activities, through exposure to different content.

3.1.1 Opinion estimation method

We developed a novel method to estimate the opinions of individuals on social media, based on available individual–content interaction data in our case study. Further details on the method can be found in Ashouri Rad (2016), but in a nutshell, we factorize the user–object (individual–news) interaction matrix into two opinion matrices (user and object) by maximizing the likelihood of observing the actual user–object matrix. Specifically, we use the idea that individuals are more likely to vote for stories that embed opinions congruent with their own, compared to content that opposes their opinions. Building on this intuition, formalized in Eq. 1, we extracted the opinions of users about content on different topics by the factorization process. Table 1 presents the notations used in this section. The basic approach we use is similar to that used in the more commonly studied case of continuous rating, e.g., for a movie rating website. In that case, if we put the data on user-movie ratings in the format of matrix R (where $R_{i,j}$ represents the rating user i assigns to movie j), we can factorize R into taste (opinion on genres of movies) matrices of users and movies, such as $R \sim U.V^T$, where: U

Table 1 Mathematical notations used in the opinion estimation method

Notation	Expression	Notation	Expression
R	User–object rating matrix	$R_{i,j}$	Rating of user i assigned to object j
W	User–object exposure probability matrix	$W_{i,j}$	The probability that object j is exposed to user i
$U_{i.}$	User i opinion vector	$U_{i,k}$	User i opinion on kth dimension
$V_{j.}$	Story j opinion vector	$V_{j,k}$	Opinion story j expresses on kth dimension
Q	Factor variables	$Q_{k,j}$	Value of kth factor for object j
α	Coefficient assigned to factor variable	α_k	Coefficient estimated for kth factor variable

(a $n \times$ k matrix) and V (a $m \times$ k matrix) represent the taste of (n) users and (m) movies, respectively, on (k) different dimensions (e.g., genres), and V^T is the transpose of matrix V. In a one-dimensional space ($k = 1$), $U_{i.}$ could be representative of user i's interest in the comedy genre, $V_{j.}$ the extent/level of comedy in movie j, and $R_{i,j}$ the rate that user i assigns to movie j based on the comedy genre.

The same intuition carries to our case of binary liking of stories (rather than a continuous rating). Specifically, we defined a utility function, $Sigmoid\left(U.V^T\right)$, where $Sigmoid\,(x) = 1/\left(1+e^{-x}\right))$ in which users gain more utility by reading stories that convey opinions close to their own (i.e., $U.V^T$ has a higher value)—see Ashouri Rad (2016) for more discussion. Building on this utility function, we developed a likelihood function for a factorization process that estimates opinion vectors of users and stories, and factorizes the interaction matrix. The factorization likelihood function (L) in our case also accounts for the likelihood that an object is observed by the user (Wi, j), and can be defined as:

$$L\,(R, W, Q) = \sum_{i=1}^{m}\sum_{j=1}^{n} Sigmoid\left(U_{i.}.V_{j.}^T + \alpha_p \times Q_{p,i,j}\right)^{R_{i,j}} \times \left(1 - W_{i,j} \times Sigmoid\left(U_{i.}.V_{j.}^T + \alpha_p \times Q_{p,i,j}\right)\right)^{(1-R_{i,j})} \quad (1)$$

where,

- $R_{i,j} = \begin{cases} 1 & \text{user } i \text{ votes for object } j \\ 0 & \text{otherwise} \end{cases}$
- $U_{i.}$ and $V_{j.}$ ($\in \mathbb{R}$) are the opinion vectors for user i and object j, respectively. Note that the number of dimensions for opinion vectors (i.e., k in $U_{n\times k}$ and $V_{m\times k}$, where n and m represent the total number of users and objects, respectively) depends on the number of opinion-based factors that could influence the user ratings of the objects (e.g., the number of different genres in rating movies).[1] In our study we use $k = 2$.

[1] Mapping the opinions in lower (than influential factors) dimensional spaces forces the factorization process to mix the effect of multiple factors on a single dimension. Yet, the computational expense of the optimization

- $Q_{p,i,j}$ represents different properties of story j which are not captured in the opinion vector for that story, (i.e., p: the number of votes, the sub-page, and location of the story in the page) but are seen by user i.
- $Sigmoid\left(U_{i.}.V_{j.}^T + \alpha \times Q\right)$ indicates the probability of user i voting for story j due to closeness of user's and object's opinions (i.e., $U.V^T$), and different properties of the object as Q (e.g., popularity of the content, visibility of the content on the website, etc.). $\alpha \in \mathbb{R}$ captures the vectors of coefficients for non-opinion mediators of votes.
- $W_{i,j}$ represents the probability that user i is exposed to object j (i.e., $W_{i,j} = 1$, where $R_{i,j} = 1$; and $W_{i,j} \leq 1$, where $R_{i,j} = 0$).

Votes are binary, and optimizing the likelihood function will estimate $U_{i.}$ and $V_{j.}$ in such a way that $Sigmoid\left(U_{i.}.V_{j.}^T\right)$ increases for voted user-story pairs ($R_{i,j} = 1$) and $\left(1 - Sigmoid\left(U_{i.}.V_{j.}^T\right)\right)$ increases otherwise ($R_{i,j} = 0$). Thus, on a one-dimensional opinion space, and ignoring other factors (Q), users and stories may share opinions that are:

- in the same direction (i.e., $U_{i.} > 0$ and $V_{j.} > 0$ or $U_{i.} < 0$ and $V_{j.} < 0$), resulting in more than 50% probability of voting (i.e., user i votes for story j with a probability higher than 50%)
- in different directions (i.e., $U_{i.} > 0$ and $V_{j.} < 0$ or $U_{i.} < 0$ and $V_{j.} > 0$), resulting in less than 50% probability of voting

In our case study, each opinion vector contains two opinion dimensions ($k = 2$), reflecting the opinions of the users and that of the stories (U_1 and U_2 for users and V_1 and V_2 for stories), as well as one fixed effect (U_3 for users and V_3 for stories). Hence:

$$U_{i.}.V_{j.}^T = U_{i,1} \times V_{j,1} + U_{i,2} \times V_{j,2} + U_{i,3} + V_{j,3} \tag{2}$$

The fixed effect for the user's opinion vector (U_3) represents the user's interest in voting in general compared to others (i.e., higher values for those who vote more frequently). For the story's opinion vector, the fixed effect (V_3) shows the attractiveness of the story (i.e., there is a higher value for stories that attract more votes regardless of the opinion they express). In our case study, we set stories posted by users as the online objects; both the user-story interaction matrix (R) and the exposure probability (W) are extracted from the data (more detail on data extraction provided in Rad and Rahmandad (2013)). We maximize the log-likelihood [of Eq. (1)] function by estimating the opinion matrices (i.e., U and V for each user and each story) and the coefficients of the factor variables (α_k):

$$\begin{aligned}
&\mathrm{Max}_{U,V,\alpha} \log\left(L\left(R, W, Q\right)\right) \\
&= \sum_{i=1}^{m}\sum_{j=1}^{n}\Big\{R_{i,j} \times \log\left(Sigmoid\left(U_{i.}.V_{j.}^T + \alpha_p \times Q_{p,i,j}\right)\right) + \left(1 - R_{i,j}\right) \\
&\quad \times \log\left(1 - W_{i,j} \times Sigmoid\left(U_{i.}.V_{j.}^T + \alpha_p \times Q_{p,i,j}\right)\right)\Big\}
\end{aligned} \tag{3}$$

Equation (3) maximizes a non-linear, smooth (has derivatives of all orders on $U, V, \alpha \in \mathbb{R}$), and continuous function. It is high-dimensional and computationally expensive. Yet, this optimization problem features a special structure that simplifies our task tremendously: All

Footnote 1 continued
increases with higher dimensions. Thus, setting the number of dimensions is a tradeoff between capturing the (most important) influential factors in separate dimensions and keeping the optimization process feasible.

local optima for this optimization reach the same payoff function, and the optimal solutions are simple transformations of each other. Specifically, there is a matrix A that converts any local optima of the factorization problem (e.g., $U.V^T$) to any other one ($U'.V'^T$): $R = U.V^T = (U.A).\left(V(A^{-1})^T\right)^T = U'.V'^T$. Therefore, simple gradient search methods can find a global optimal solution, from which all the other optimal solutions are reachable (see Ashouri Rad (2016) for more detail). Based on these key characteristics of the problem and our study of different optimization algorithms, we used the limited memory BFGS (L-BFGS) optimization algorithm (Liu and Nocedal 1989) for the optimization step which we found effective for solving the problem.

Maximizing the likelihood function (Eq. 3) based on the data, which was collected from our case study platform using a history reconstruction algorithm (Rad and Rahmandad 2013), we estimated the opinion vectors of users and stories (as well as coefficients of factor variables (α)) on weekly time windows from August 2006 to May 2008 on a two-dimensional opinion space. Opinion vector values were estimated for all the active users and active stories (i.e., users who cast votes and stories that received votes) in each time window. This process provided us with 6151 user-week opinion vectors and 287,327 story opinion vectors. The estimation was conducted on a computer with a CPU of 2.1 GHz and 16 cores, which took approximately 2000 h of computation.

By studying estimated opinion values for stories in a case study, Ashouri Rad (2016) presented 2-dimensional opinion vectors, where the first dimension (i.e., U_1 for users and V_1 for stories) represents support for, or opposition to, the Iranian government (on positive and negative sides of the axis, respectively). The second dimension (i.e., U_2 for users and V_2 for stories) represents a mixture of other features of stories (related to tone and style) that affect the voting of users, in which having rich media (i.e., picture, video, and audio), language of the content (informal vs. formal), expressing personal opinion, and having entertaining content are the most important explanatory features of in this second dimension. For the sake of simplicity, we refer to stories containing rich media, personal opinion, with informal language or entertaining content, which often use eye-catching rather than well-researched news, as 'yellow' stories. We refer to the other broad group of stories (including non-yellow content) as 'green' stories. The opinion values of yellow stories (and their fans) lie on the negative side of the second opinion dimension, while the opinion values for green stories (and their fans) lie on the positive side (see Ashouri Rad (2016) for more details). Figure 1 presents the combinations of different opinions and stories studied in this research.

3.1.2 Regression analysis

Table 2 presents the notations used in regression analysis.

In this section, we discuss how we studied the effects of interacting with different opinions on individual activities using linear regression modeling. We focused on three main activities (posting, revisiting, and commenting) and developed a regression model for each. These models measure the effects of reading stories on user activities, based on the story's and user's opinion regarding the Iranian government and being a fan of yellow/green stories (see Fig. 1). As discussed earlier, we estimated users' and stories' opinion values in weekly time windows. We report the results from a linear regression because the number of activity events are large enough that a linear regression offers a very good approximation with more intuitive coefficient values. Results are robust to using a Poisson regression model.

To study the effect of interaction with different opinions on user activities, we measured the changes in user activity, i.e., the number of stories posted, the number of revisits, and

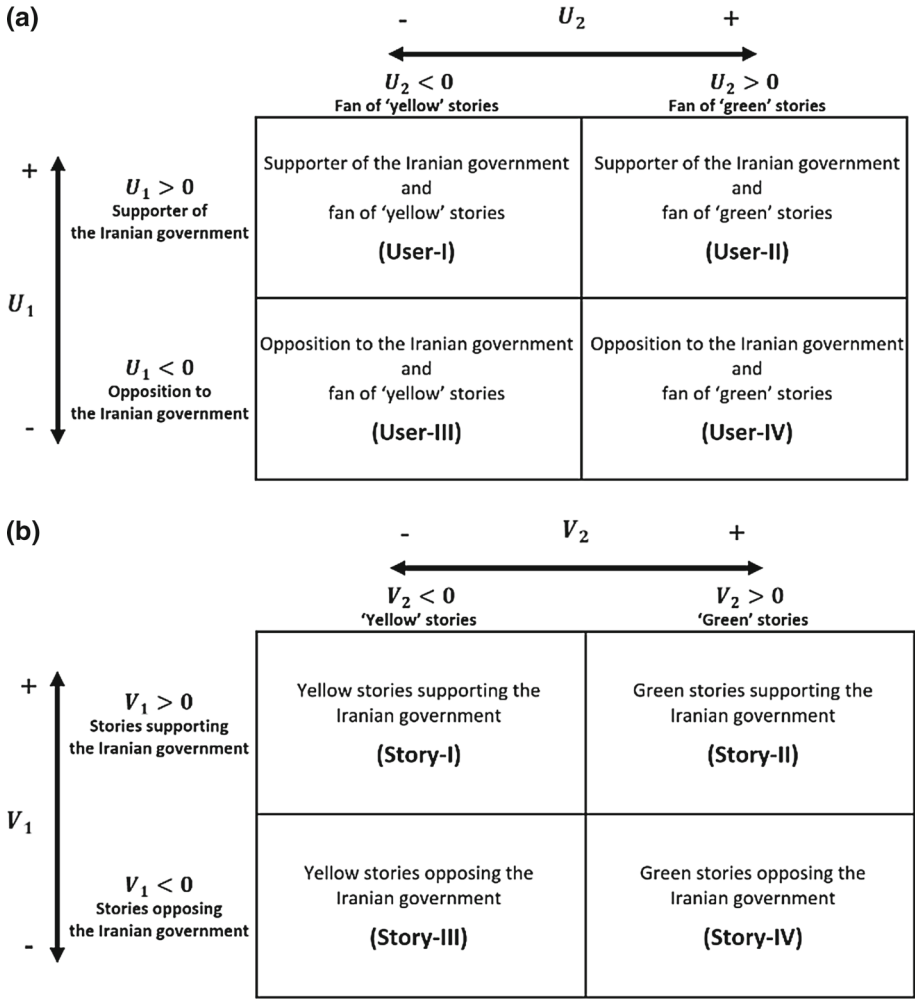

Fig. 1 **a** Combination of different opinions based on U_1 and U_2; **b** combination of different stories based on V_1 and V_2

Table 2 Mathematical notations used in regression analysis

Notation	Expression
T_i	Number of weeks since user i joined the website
γ_i	Fixed effect assigned to user i
β_0	Intercept
$\beta_{l=1\,to\,16}$	Effect of reading stories in group l on changes in user activity change
β_p	Effect of posting stories on user activity
β_c	Effect of publishing comments on user activity
n	The total number of users
m	The total number of online objects
L	Likelihood function

the number of comments. These changes were measured in two separate weeks, h weeks apart. We then estimated the effect of opinions on the changes based on the cumulative utility (defined below) users had gained from reading stories within the intervening h weeks. Based on our data set, we estimated h to be 23 weeks, considering a tradeoff between the between-week duration and the number of data points; we needed a long duration to study the behavior of users, but the longer the duration, the fewer users and data points.[2] We use a sliding window method, moving forward the time window by one week and recording the independent and dependent variables for each new week.

We recorded the utility from consuming the content in the intervening weeks (as an independent variable) and the change in activity (as a dependent variable) to fit the regression model. For instance, we calculated the change in the number of revisits between weeks 1 and 25 (i.e., $Revisit_{i,t+25} - Revisit_{i,t}$ in Eq. (4)), and measured the sum of the utility gained in weeks 2 to 24 from reading stories. Then, we moved the time window one week forward and calculated the change between weeks 2 and 26 and measured the utility in weeks 3–25, and so forth. We continued collecting the data in this manner for all users during the total of 87 active weeks.

In each of the three regression models, we set a fixed effect (γ) for user baseline activity change, to measure the average change in user activity based on factors independent of what they read. We also controlled for the number of weeks (T) since users had joined the website, to assess the effect on user activity of being a newcomer vs. being an old-timer in the community.

We categorized each user-story pair into one of the 16 different groups based on the polarity (sign) of the opinion of the story and user with regard to the Iranian government and yellow or green content/fans; all possible combinations of $U_1 < 0$, $U_1 > 0$, $V_1 < 0$ and $V_1 > 0$ result in 16 groups (see Table 7 for the structure of the three regression models based on these 16 groups). If we assume user i, who is a supporter of the government ($U_{i,1} > 0$) and is a fan of yellow stories ($U_{i,2} < 0$), reads story j that opposes the Iranian government ($V_{j,1} < 0$) and is yellow ($V_{j,2} < 0$), then the user i-story j pair lies in the group that represents $U_1 > 0$, $V_1 < 0$, $V_2 < 0$, $U_2 < 0$ (i.e., group 8 in Table 7).

We measured the marginal utility the user gained from reading each story using $sigmoid\,(K) - 0.5$, where $K = U_1 \times V_1 + U_2 \times V_2 + V_3$, U_1 and U_2 are the user's opinion values, V_1 and V_2 are the story's opinion values, and V_3 is the attractiveness of the story (i.e., the story's fixed effect). We then calculated cumulative gained utility on each of the groupings as one independent variable in the regression models. This leads to a total of 16 coefficients ($\beta_1 - \beta_{16}$) that capture how various pairs of user-story types may have a different type of impact on the user's activity. Here, the marginal utility gained by reading a story is the result of comparing (i.e., subtracting) the total utility the user gains from reading the story ($sigmoid\,(K)$) with the utility she gains from reading a completely neutral story (i.e., $sigmoid\,(K = 0) = 0.5$).[3] Thus, when a user reads a story that contradicts her opinion (e.g., a User-II reads a Story-III—see Fig. 1—with zero attractiveness), the result of the subtraction

[2] The number of 'between-weeks' was optimized using the F-test on the first regression model (on posting), and we chose the number of in-between weeks based on the p-value. Note that since the number of variables (user and time-fixed effects) and the number of datasets change with different 'between weeks' values, we cannot use R^2, Akaike information criterion (AIC), or log-likelihood value for this comparison. $sigmoid\,(K = 0) = 0.5$ implies that the story is not biased toward any of the groups (supporter/opposition and yellow/green), and the story's attractiveness is zero: The story is neither attractive nor unattractive in obtaining votes.

[3] $sigmoid\,(K = 0) = 0.5$ implies that the story is not biased toward any of the groups (supporter/opposition and yellow/green), and the story's attractiveness is zero: The story is neither attractive nor unattractive in obtaining votes.

is negative, indicating that the user does not gain the expected utility by reading that story. In essence, the user gains less utility by reading that story compared to when she reads a story that is not about the government at all. In other words, considering the time and energy the user spends in reading the story, she gains less utility than her expectation. Therefore, the marginal utility implies the difference between gained and expected utility, which could be either negative or positive. Following this assumption, the regression model for revisiting, as an example, is defined as:

$$\begin{aligned} Revisit_{i,t+25} - Revisit_{i,t} &= \beta_0 \\ &+ \beta_{l=1\,to\,16} \sum_{k=t+1}^{t+24} \sum_{j \in \Psi_{i,k,l}} (sigmoid\,(K) - 0.5) + \beta_p \sum_{k=t+1}^{t+24} Posts_{i,k} \\ &+ \beta_c \sum_{k=t+1}^{t+24} Comments_{i,k} + \gamma_i + T_i \end{aligned} \tag{4}$$

where,

- $Revisit_{i,t+25} - Revisit_{i,t}$ represents the change in the number of times user i revisited the website between weeks t and $t + 25$.
- $\Psi_{i,k,l}$ represents the set of stories belonging to opinion group l (considering the opinion of user i) that user i read in week k.
- β_0 is the intercept of the model. For the sake of decreasing the complexity of the models, we assumed that β_p is the same for all 16 groups.
- γ_i is the user fixed effect (i.e., one dummy variable for each user) for user i and T_i, which is the number of weeks since user i joined the website (i.e., one dummy variable for each week).
- $\sum_{k=t+1}^{t+24} Posts_{i,k}$ and $\sum_{k=t+1}^{t+24} Comments_{i,k}$ are the number of stories and comments, respectively, user i published in the weeks between $t + 1$ and $t + 24$.

We extracted the effect of opinions by summing the marginal utility (i.e., $sigmoid\,(K) - 0.5$) the user gained by reading stories in each group, where β_l captures the effect of reading stories in group l on user's activity change; note that we have $l = 1\,to\,16$ as the opinion groups. We used the same model for the change in the number of posted stories and published comments: We removed $\sum_{k=t+1}^{t+24} Posts_{i,k}$ and $\sum_{k=t+1}^{t+24} Comments_{i,k}$ for the posting and commenting models, respectively.

Data on posting stories and comments are directly available in our datasets. However, to extract the data on the stories each user reads and revisiting data, we used a novel history reconstruction method introduced by Rad and Rahmandad (2013). In short, we recreated the history of each action (i.e., posting, revisiting, and commenting) of users based on a heuristic minimization model and the ranking algorithm of the website. Thus, we can recreate a snapshot of the website (i.e., stories in each sub-page and ordering page, promotion status of the stories, etc.) at any time a user has voted for a story and estimate the stories she reads based on her location on the website (i.e., ordering page, sub-page, and place in the sub-page where the user voted for the story) (see Rad and Rahmandad (2013) for more details on this method).

Based on our case study data, we estimated the three regression models. In Sect. 4.1, we present the results and discuss the mechanisms that change user activities on the website. Next, we present an agent-based simulation model to study the formation of communities in our case study as a result of user interactions with different opinions.

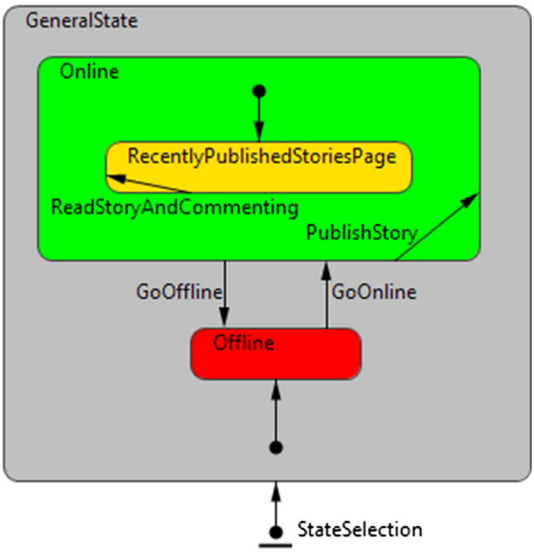

Fig. 2 Transitions between online and offline states

3.2 Simulation model

The regression analysis above focused on the impact of consuming different types of opinions on user activity. However, in a system where individuals affect each other, and there are interdependencies among the variables, regression equations do not directly inform the system level outcomes. To study and understand the evolution of such a nested system, we developed an agent-based model that simulates the behaviors and activities of the users and the formation of communities as a result of user interactions with opinions of others.

Following our case study, we modeled a simplified version of the social news websites on which users can get online, publish posts, and comment on other posts. We considered two different general states for the users: online and offline. The online state equates to visiting the website, where users can read stories, post new stories, and comment on stories they read. Figure 2 presents the states and transitions between the two states for each simulated user. Tables 3, 4, and 5 describe the notations we use for the simulation parameters, functions, and states in this section.

Users, as agents in the simulation, change their state from offline to online through a T_{Online} transition with the rate of R_{Online}. In the online state, users can either publish a new story (using T_{Post} transition) or visit the ordering page (S_{Page}) and read stories (through T_{Read} transition). Users go offline after spending a certain amount of time (with duration D_{Online}) on the website through a $T_{Offline}$ transition. Table 6 presents the transition triggers and the pseudocodes for each transition.

Users can visit the website on a daily basis with the rate R_{Online}. When the user is online, she can check out new stories (i.e., starting from the top of the ordering page, the user looks for a story she has not read before through $F_{Search\ Story}$) with the rate of R_{Read}. Her activity (R_{Online}, $R_{Comment}$, or R_{Post}) updates based on the opinion and attractiveness of the story ($s_{Opinion\,1}, s_{Opinion\,2}, s_{Attractiveness}$) that she reads through $F_{Set\ Activity}$. Then she decides whether to comment on the story based on her $R_{Comment}$ (see $F_{Comment}$ in the Online Supplementary Materials, Table S1). Finally, the story will be marked as read for the user (using $F_{Set\ As\ Read}$ procedure).

Table 3 Parameter notation and initial values

Parameter	Notation	Value/initial value
CommentRate	$R_{Comment}$	0
OnlineRate	R_{Online}	1 per day
PostingRate	R_{Post}	0
ReadingRate	R_{Read}	44 per hour
OnTimeAverage	D_{Online}	38 minutes
UserNumberOfGettingOnlineThisWeek	N_{Online}	0
UserOpinionDim1	$u_{Opinion\,1}$	$N\left(\mu = 0, \sigma^2 = 1\right)$
UserOpinionDim2	$u_{Opinion\,2}$	$N\left(\mu = 0, \sigma^2 = 1\right)$
UserActivity	$u_{Activity}$	$N\left(\mu = 0, \sigma^2 = 1\right)$
StoryOpinionDim1	$s_{Opinion\,1}$	$u_{Opinion\,1}$ of publisher
StoryOpinionDim2	$s_{Opinion\,2}$	$u_{Opinion\,2}$ of publisher
StoryAttractiveness	$s_{Attractiveness}$	$N\left(\mu = 0, \sigma^2 = 1\right)$
UserNumberOfPublishedStoriesThisWeek	N_{Post}	0
PostsEffectOnOnlineRate	$\beta_{P,Online}$	From regression results
PostsEffectOnCommentRate	$\beta_{P,Comment}$	From regression results
CommentsEffectOnPostRate	$\beta_{C,Post}$	From regression results
CommentsEffectOnOnlineRate	$\beta_{C,Online}$	From regression results
OpinionEffectOnPostRate	$\beta_{Opinion\ Group,Post}$	From regression results
OppinionEffectOnOnlineRate	$\beta_{Opinion\ Group,Online}$	From regression results
OppinionEffectOnCommentRate	$\beta_{Opinion\ Group,Comment}$	From regression results
LifeCycleOfStoryInRecentlyPublishedPage	$D_{Story\ Life\ Cycle}$	1 day
ReadStoriesID	$u_{\{Stories\ Read\}}$	Empty

Table 4 Function and procedure notation

Function/procedure	Notation
AddStory()	$F_{Add\ Story}$
CommentForStory()	$F_{Comment}$
EmptyReadStories()	F_{Empty}
EmptyReadStories()	$F_{Release\ Memory}$
Remove()	F_{Remove}
SearchForNewStory()	$F_{Search\ Story}$
SetActivity()	$F_{Set\ Activity}$
SetBoundaries()	$F_{Set\ Boundaries}$
SetStoryAsRead()	$F_{Set\ As\ Read}$
Sigmoid()	$sigmoid$

Users can also publish stories with the rate R_{Post}/D_{Online}, where D_{Online} is the duration for which the user browses the website in each of her online sessions, and R_{Post} is the average number of stories the user publishes during that duration. When the user makes a posting, her story will be added to the system with the same opinion as the publisher (through the

Table 5 State names and notations

State name	State notation	Parent-state
GeneralState	S_G	–
Offline	$S_{Offline}$	GeneralState
Online	S_{Online}	GeneralState
RecentlyPublishedPage	S'_{Page}	–
RecentlyPublishedStoriesPage	S_{Page}	Online

Table 6 Transition triggers and the pseudocodes

Transition name	Transition notation	Trigger	Pseudocode
GoOnline	T_{Online}	R_{Online}	$N_{Online} = N_{Online} + 1$
ReadStoryAnd Commenting	T_{Read}	R_{Read}	$s = F_{Search\ Story}$
			$F_{Set\ Activity}\left(s_{Opinion\,1}, s_{Opinion\,2}, s_{Attractiveness}\right)$
			$F_{Comment}\left(R_{Comment}\right)$
			$F_{Set\ As\ Read}\left(s\right)$
PublishStory	T_{Post}	R_{Post}/D_{Online}	$F_{Add\ Story}\left(u_{Opinion\,1}, u_{Opinion\,2}\right)$
			$N_{Post} = N_{Post} + 1$
			$R_{Online} = R_{Online} + \beta_{P,Online};$
			$R_{Comment} = R_{Comment} + \beta_{P,Comment}$
			$F_{Set\ Boundaries}$
GoOffline	$T_{Offline}$	D_{Online}	F_{Empty}
KillStory	$T_{Dispose\ Story}$	$D_{Dispose}$	$F_{Remove}\left(s\right)$

$F_{Add\ Story}$ procedure) and will be placed at the top of S_{Page}. Then, the R_{Online} and $R_{Comment}$ will be updated based on the effect they get from posting a story. After each update in activity, we check the rates for any violation in the boundaries[4] (in $F_{Set\ Boundaries}$ procedure). Finally, after a certain amount of time (D_{Online}), the user leaves the website and the memory assigned to the story she read is released[5] (through F_{Empty}). For simplification, we ignored the voting mechanism and assumed a system that keeps posted stories for one day and sorts the stories in chronological order, similar to the ordering page of recently published stories on the website.

The parameter values for user agents provided in Table 3 (R_{Read} and D_{Online}) are estimated from the data. For other parameters, as the baseline, we assumed a normally distributed community. In Sect. 4.2, we discuss sensitivity analysis on these parameters and present the results of changing these parameters on the formation of communities. By changing the mean value of user opinion distributions, we study the effect of interacting with a variety of opinions in asymmetric (i.e., biased) communities on user activity. Additionally, by changing the standard deviation of the distributions, we examine the effect of the communities'

[4] We assumed that users will not publish more than 100 stories per day, post more than 500 comments, or visit the website more than 5 times. We conducted a sensitivity analysis and the overall dynamic behavior of the results is not sensitive to these assumed values. These rates cannot be negative, either.

[5] Due to the short life cycle of stories (i.e., one day) and the range of online rate of users in our case study platform (i.e., less than one time per day), releasing the memory does not have any significant effect; however, in other platforms this assumption may be violated.

opinion being extreme or neutral (toward supporting or opposing the Iranian government) on user activity. Furthermore, by changing the mean of the stories' fixed effects distribution (i.e., $s_{Attractiveness}$), we study the effect of story attractiveness on the activities. Again, the attractiveness of a story represents the extent to which it can attract votes, regardless of the opinion it expresses (measure by the fixed effect, V_3).

$F_{Set\ Activity}$ updates R_{Post}, R_{Online} and $R_{Comment}$ of the user based on the opinion of the story she read, using the following equations:

$$R_{Post,\ t+1} = R_{Post,\ t} + \beta_{Opinion\ Group,Post} \times \left(sigmoid\left(K'\right) - 0.5\right) \tag{5}$$

$$R_{Online,\ t+1} = R_{Online,\ t} + \beta_{Opinion\ Group,Online} \times \left(sigmoid\left(K'\right) - 0.5\right) \tag{6}$$

$$R_{Comment,\ t+1} = R_{Comment,\ t} + \beta_{Opinion\ Group,Comment} \times \left(sigmoid\left(K'\right) - 0.5\right) \tag{7}$$

where, $K' = u_{Opinion\,1} \times s_{Opinion\,1} + u_{Opinion\,2} \times s_{Opinion\,2} + s_{Attractiveness}$. In Eqs. (5), (6), and (7), we basically calculate the marginal utility value that the user gains by reading the story (i.e., $\left(sigmoid\left(K'\right) - 0.5\right)$), and derive its effect on the user's activity change, considering the respective opinion group (i.e., in the same way we calculate the regression independent variable in Eq. (4)).

For simplification, in our simulation model we assumed that there was only one ordering page (S'_{Page}) so that when a story is posted, it is placed at the top of this ordering page. The life cycle of stories on this ordering page ($D_{Story\ Life\ Cycle}$) is assumed to be one day. $T_{Dispose\ Story}$ transition removes the story from the ordering page (and the system) when it reaches the end of its life cycle (i.e., one day for recently published ordering pages). The results of the simulation model are presented in Sect. 4.2.

4 Results

We first present the results of regression modeling analysis in Sect. 4.1, and then discuss the results of simulation analysis in Sect. 4.2.

4.1 Regression results

Using the history reconstruction and opinion estimation methodology discussed, we estimated the coefficients in the models based on our case study data. Table 7 presents estimated coefficients and their change directions in the three mechanisms of posting, revisiting, and commenting. We discuss the results in detail below, but to summarize, all of the opinion groups post more often after reading stories with the same viewpoint as their own. All groups visit the website less frequently and they post less often (except the 10th group), but publish more comments (except the 11th group), after reading contrary opinions. Additionally, users publish more comments after posting stories, but post less after publishing comments. Users also post more often, on average, but revisit less frequently over time.

The results of the three mechanisms (posting, revisiting, and commenting) are discussed in more detail below.

4.1.1 Posting mechanism

The increase or decrease in user activity depends on the sign of the estimated coefficient and K (where $K = U_1 \times V_1 + U_2 \times V_2 + V_3$). For positive K, the marginal utility of reading the story (i.e., $sigmoid\,(K) - 0.5$) is positive. Thus, for positive coefficient ($\beta_l > 0$), positive

Table 7 Extracted mechanisms of user activity through results of the regression models

Variable	Description (see Fig. 1)	Configuration		Regression Results					
				Change direction after the 24-week period†			Estimates		
		U	V	Regression 1	Regression 2	Regression 3	Regression 1	Regression 2	Regression 3
				Posting	Revisiting	Commenting	Posting	Revisiting	Commenting
User and Story in the same quadrant									
β_1	User-II on Story-II	$U_1 > 0, U_2 > 0$	$V_1 > 0, V_2 > 0$	↑	↓	↓	0.0086**	−0.0011**	−0.0103**
β_{16}	User-III on Story-III	$U_1 < 0, U_2 < 0$	$V_1 < 0, V_2 < 0$	↑	–	-	0.0077**	0.0000	0.0001
β_4	User-I on Story-I	$U_1 > 0, U_2 < 0$	$V_1 > 0, V_2 < 0$	↑	–	↑	0.0055*	0.0000	0.0069*
β_{13}	User-IV on Story-IV	$U_1 < 0, U_2 > 0$	$V_1 < 0, V_2 > 0$	↑	–	↓	0.0063*	−0.0002	−0.0118**
User and Story in the opposite quadrant									
β_{10}	User-III on Story-II	$U_1 < 0, U_2 < 0$	$V_1 > 0, V_2 > 0$	–	↓	↑	0.0002	0.0022**	−0.0096**
β_7	User-II on Story-III	$U_1 > 0, U_2 > 0$	$V_1 < 0, V_2 < 0$	↓	↓	↑	0.0012**	0.0024**	−0.0207**
β_6	User-I on Story-IV	$U_1 > 0, U_2 < 0$	$V_1 < 0, V_2 > 0$	↓	↓	↑	0.0012*	0.0018**	−0.0158**
β_{11}	User-IV on Story-I	$U_1 < 0, U_2 > 0$	$V_1 > 0, V_2 < 0$	↓	↓	-	0.0014**	0.0013*	0.0018
Other combinations									
β_2	User-I on Story-II	$U_1 > 0, U_2 < 0$	$V_1 > 0, V_2 > 0$	–	–	-	−0.0010	0.0000	0.0009
β_8	User-I on Story-III	$U_1 > 0, U_2 < 0$	$V_1 < 0, V_2 < 0$	–	–	-	−0.0008	0.0001	0.0005
β_3	User-II on Story-I	$U_1 > 0, U_2 > 0$	$V_1 > 0, V_2 < 0$	–	–	↓ / ↑	0.0003	0.0000	0.0047*
β_5	User-II on Story-IV	$U_1 > 0, U_2 > 0$	$V_1 < 0, V_2 > 0$	↓ / ↑	–	-	0.0014**	0.0000	0.0004
β_9	User-IV on Story-II	$U_1 < 0, U_2 > 0$	$V_1 > 0, V_2 > 0$	↓ / ↑	–	-	0.0016**	−0.0001	0.0002

Table 7 continued

Variable	Description (see Fig. 1)	Configuration		Regression Results					
				Change direction after the 24-week period†			Estimates		
		U	V	Regression 1	Regression 2	Regression 3	Regression 1	Regression 2	Regression 3
				Posting	Revisiting	Commenting	Posting	Revisiting	Commenting
β_{15}	User-IV on Story-III	$U_1 < 0, U_2 > 0$	$V_1 < 0, V_2 < 0$	–	–	-	0.0008	0.0001	0.0003
β_{12}	User-III on Story-I	$U_1 < 0, U_2 < 0$	$V_1 > 0, V_2 < 0$	↑ / ↓	–	↑ / ↓	−0.0010**	0.0002	−0.0055*
β_{14}	User-III on Story-IV	$U_1 < 0, U_2 < 0$	$V_1 < 0, V_2 > 0$	–	↑ / ↓	-	−0.0011	−0.0004*	0.0008
β_c	Comments			↓	–	-	−0.0007**	0.0000	–
β_p	Posts			–	–	↑	–	0.0000	0.0117
β_0	Intercept						0.8086**	−0.0901**	0.6015
$R^2_{(c)}$	Conditional R-squared						0.41	>0.1	0.13
$R^2_{(m)}$	Marginal R-squared						0.14	>0.1	0.05
n	Data points						51191	51191	51191
p	p-value						0.00	0.00	0.00

* $P < 0.05$; ** $P < 0.01$

† Only statistically significant results ($P<0.05$) are presented where: ↑: increase in the activity; ↓: decrease in the activity; ↑ / ↓: increase or decrease in the activity depending on the values of U and V

K implies that $(sigmoid\,(K) - 0.5) \times \beta_l > 0$. Therefore, increases in the marginal utility result in increasing user activity (and vice versa). On the other hand, for negative K, the marginal utility is negative, and the positive coefficient implies a decrease in user activity. Building on this and following the statistically significant results reported in Table 7, it can be summarized that:

- The positive values estimated for coefficients β_1, β_4, β_{13} and β_{16} indicate that all the opinion groups post more frequently after reading posts with the same viewpoint as their own.[6]
- Reading stories with contrary opinions (e.g., Users-II reading Story-III) reduces the posting rate for all the groups except Users-III, yellow opposition, for whom the effect is insignificant (i.e., β_6, β_7 and β_{11} estimated to be positive and statistically significant, while β_{10} is insignificant).[7]
- The positive values estimated for β_5 and β_9 indicate that fans of green stories (Users-II and Users-IV) post more stories reading green opponent stories (Stories-IV and Stories-II, respectively), if it increases their utility (i.e., if the utility gained from the 'greenness' of the content overcomes the decrease in utility caused by opposing or supporting the government), and post less otherwise.[8]
- β_{12} is estimated to be negative, which implies that Users-III, yellow opposition, post more stories after reading Stories-I, yellow supporter, if it increases their utility (i.e., if the utility gained from the 'yellowness' of the content overcomes the decrease in utility caused by supporting the government), and post less otherwise.[9]

A positive significant intercept indicates that on average the number of posts increases, regardless of what users read on the website. This change in the posting rate varies between different users ($\sigma_{users\ random\ effect} = 0.952$), but the number of weeks that have passed since the user started using the website (i.e., the time fixed effect) has no significant effect on posting. A negative significant coefficient for the number of published comments indicates that the posting rate decreases when a user publishes more comments. This could be the result of users becoming frustrated and discouraged when they participate in heated discussions on platform.

The conditional R-squared and marginal R-squared of the regression model are 0.41 and 0.14, respectively, meaning that the model explains 41% of the variability in the data, while the fixed effect alone explains 14% of the variability.

4.1.2 Revisiting mechanism

Most of the coefficients in the regression model for the revisiting mechanism are not statistically significant (see Table 7), so one could infer that what users read on the website has a

[6] Hence, for all the opinion groups, gaining utility by reading stories with the same point of view increases the posting rate.

[7] Note that a greater difference between the opinion of the user and that of the stories she reads results in a further decrease in her utility and posting rates. For instance, when a User-II reads a Story-III, her posting rate decreases more than when she reads a Story-III which is more neutral toward opposing the government.

[8] In other words, reading green stories (Story-II or Story-IV) that are somehow more neutral (i.e., not extreme in opposing/supporting the government) increases the posting rate of green users (User-II or User-IV). However, reading green extreme opponent stories (User-IV reading Story-II or User-II reading Story-IV) reduces user posting rates, implying that they become discouraged about sharing their opinions when they read stories with opinions differing widely from their own with regard to the government (i.e., when they feel the opinions of their audiences are very different from theirs).

[9] Unlike in the previous cases, here Users-III confront opinions of Users-I who are extreme in supporting the government by posting more stories.

limited effect on their likelihood of revisiting the website. However, due to the lack of data on exact times of online visits, our results on this variable are more tentative.[10] We discuss the significant results below:

- Negative β_1 signifies that reading like-minded stories decreases Users-II's (green supporter) online rate, which means they return less frequently after reading Stories-II.
- β_6, β_7, β_{10} and β_{11} are all estimated to be positive, implying that all of the opinion groups revisit the website less often after reading stories from users with opposing opinions (e.g., Users-II reading stories from Stories-III). This could be the result of users becoming frustrated by reading stories that are incompatible with their opinions.
- A negative β_{14} implies that Users-III revisit the website more often upon reading Stories-IV that decrease their utility (i.e., if the utility loss from the 'greenness' of the content overcomes the increase in utility caused by opposing the government), and revisit less otherwise.

A negative significant intercept indicates that users' online rate decreases on average over time, but the scale varies (slightly) based on the number of weeks that have passed since the user joined the website ($\sigma_{time\ random\ effect} = 0.059$). There is limited variation in the change of online rates between different users. Note that posting is conditional on users being online; consequently, positive and negative intercepts for posting and online rate, respectively, imply that users revisit the website less frequently over time, but in each online session they post more stories. Additionally, the number of published posts and comments has no effect on the online rate.

Conditional and marginal R-squared are both less than 0.01, which means that the model explains less than 1% of the variability in the data. Therefore, the change in users' online rates is mostly affected by other variables (possibly exogenous factors) not considered in our model.

4.1.3 Commenting mechanism

The statistically significant results for the commenting regression (see Table 7) are summarized as follows:

- Negative β_1 and β_{13} imply that green users (User-II and User-IV) comment less when they read stories with the same opinion as theirs (Story-II and Story-IV, respectively). This means that, for green users, reading stories with the same viewpoint as theirs decreases their willingness or need to participate in discussion.
- A positive β_3 presents that the comment rate for Users-II decreases when they read Stories-I that decrease their utility (i.e., if the utility loss from the 'yellowness' of the content overcomes the increase in utility caused by supporting the government), and the comment rate increases otherwise.
- A positive β_4 presents that Users-I comment more after reading stories with the same viewpoint as their own.
- Negative β_6 and β_7 indicate that Users-I and Users-II become more engaged in discussions after reading Stories-IV and Stories-III, respectively.
- β_{10} is negative, meaning that Users-III comment more after reading Stories-II.
- A negative β_{12} implies that Users-III comment more after reading Stories-I that decrease their utility (i.e., if the utility loss from supporting the government overcomes the increase in utility caused by 'greenness' of the content), and comment less otherwise.

[10] As noted earlier, we had raw data for comments and posts but estimated the time of online visits—see Ashouri Rad (2016) for more information.

The estimated intercept value is not significant; hence, there is no constant change in the number of comments over time. However, the change in the number of comments varies for different users and times since joining the website (based on $\sigma_{user\ fixed\ effect} = 0.830$ and $\sigma_{time\ fixed\ effect} = 0.886$, respectively). Also, the number of posts the user publishes has a positive effect on her number of comments. This could be due to the users' contributions in discussions on their posted stories.

Conditional R-squared of the online rate regression model is 0.13, while its marginal R-squared is 0.05; i.e., the model explains 13% of variability in the data, while fixed effects alone explain only 5% of the variability.

4.2 Simulation results

In this section, as a baseline scenario, we first present simulation results for a symmetric (i.e., unbiased) community that does not have a significant tendency to support or oppose the Iranian government, and to be fans of yellow or green stories (Sect. 4.2.1); the mean values of the starting points of $u_{Opinion\,1}$ and $u_{Opinion\,2}$ are set to be zero. We discuss the evolution of this community over time, considering the three mechanisms of posting, revisiting, and commenting. Then, by changing the mean starting points of $u_{Opinion\,1}$, we are able to study the behavior and the future formation of biased communities (see Sect. 4.2.3).

4.2.1 Symmetric community

First, we simulate 500 hypothesized users with standard-normally distributed opinions (on two dimensions in Fig. 1: supporting/opposing the Iranian government, and being fans of yellow and green stories), as well as stories' attractiveness (N (0, 1)) for 1000 days[11]. Based on our data, we assume that the distribution of opinions is normal; however, this assumption can be violated in other data sets. The total number of weekly posts and the average (weekly) posts in each quadrant—see Fig. 1 for the descriptions of each quadrant—are provided in Figs. 3 and 4, respectively.

Figures 3 and 4 show that the total and average posts (for all the opinion groups) have bell-shaped trends, with different skewness and peak values for each of the quadrants. Therefore, in a symmetric community, users in all opinion groups start losing interest in activity on the website (i.e., revising the website and posting stories) after reaching a peak. This means that, if we assume no new users join the community, a platform with this structure is doomed to gradual failure.

Analyzing posting and online rates (see Online Supplementary Materials, Fig. S1 and Fig. S2), it can be seen that posting rates, on average, increase over time in all the quadrants; however, a constant decline in the online rate limits the number of posts published by users. In other words, over time users tend to post more stories during each of their online sessions, but the number of online sessions declines. The interaction of these two effects leads to the nonlinear relationship observed in total activity (Fig. 3), with an initial increase and a longer-term decline.

[11] Basically, based on the structure of our simulated social media website (in which stories have a one-day life cycle and are sorted based on their time of publication), for consistent results we need to have enough new stories for each user to read in each online session. The R_{Read} and D_{Online} of users determine the number of new stories we need in the system for consistent simulation results and, considering parameter values (Table 3), 500 users generate enough new stories for all users to read. Communities may fizzle out due to lack of content for significantly smaller user bases.

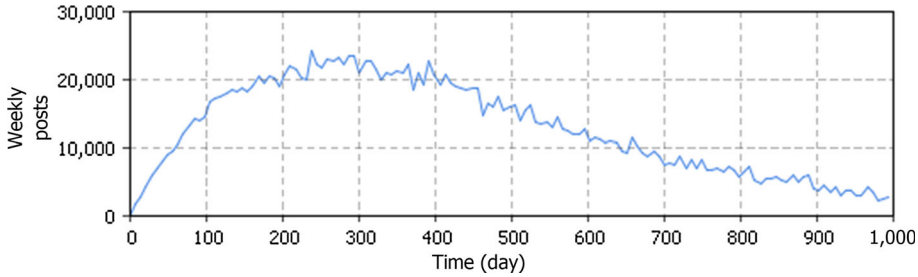

Fig. 3 Total weekly posts for a symmetric community simulated over 1000 days

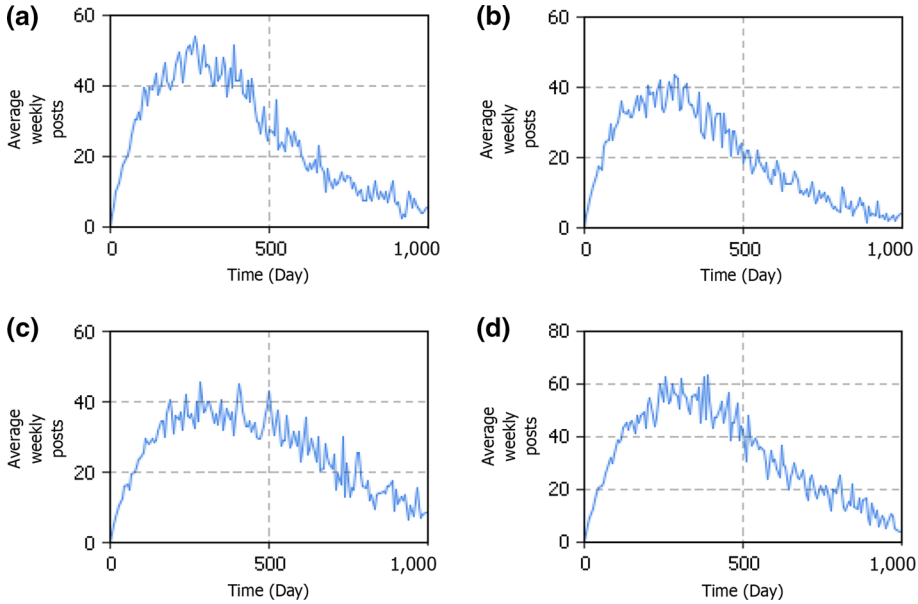

Fig. 4 Average weekly posts in each quadrant simulated for a symmetric community over 1000 days. **a** Users-I: supporter of the Iranian government and fan of yellow stories. **b** Users-II: supporter of the Iranian government and fan of green stories. **c** Users-III: oppositions of the Iranian government and fan of yellow stories. **d** Users-IV: oppositions of the Iranian government and fan of green stories

For all opinion groups, the bell-shaped trend for average weekly posts (Fig. 4) is the result of an increase in posting at first, and then a decrease in revisiting. However, the skewness and peak of the average weekly posts vary across different groups, due to other mechanisms in the system. Among users who are fans of green stories, Users-II (unlike Users-IV) visit the website less frequently after reading stories with the same opinion as their own. As a result, the peak of the average weekly posts for that group ends up being lower than that of the opposition, whose posting rate also declines faster. Such mechanisms can influence the future formation of opinions on the platform. We will discuss similar mechanisms in the next section.

The total and average for published comments (see Online Supplementary Materials, Fig. S3 and Fig. S4) have similar skewed bell-shaped trends as well. Again, the comment rate follows a rising pattern (see Online Supplementary Materials, Fig. S5) and the online rate

caps the number of published comments. Therefore, over time, users publish more comments during each online session, but total comments decrease due to participating in fewer online sessions.

In general, the decreasing online rate in all four groups (see Online Supplementary Materials, Fig. S2, and the estimated negative intercept for the online rate regression in Table 7) is likely to occur because users become tired of the community, regardless of their opinion and that of the community. Furthermore, the fact that the numbers of posts and comments are estimated to be non-significant (in the revisiting regression) shows that user activity rates have little effect on users eventually becoming tired of the community and ultimately leaving the system.

4.2.2 Assessment

To assess the results of the baseline simulation, we compared them with a subset of case study data for 133 users who were active on the website for at least six months. We particularly focused on the data for the posting mechanism, based on the attractiveness of fit of the posting regression model compared with the models of the other two mechanisms (see Table 7). Based on the extracted data, we calculated the time trend for the weekly average posts for the duration of user activity, starting from the time each user joined the website. We then simulated our model 50 times for 500 hypothesized users with standard-normally distributed opinions; however, we set the stories' attractiveness to the estimated value for the case study community ($\mu = -3.55, \sigma = 1$) (see Ashouri Rad (2016) for more information). We then calculated the 95% confidence interval of the simulated average weekly posts and compared it with the trend we extracted from the data.

Comparing the average weekly posts of the selected users with that of the simulations, 85% of the data points fall in the simulated 95% confidence interval. The trend extracted from the data lies slightly above the 95% confidence interval during the first 10 weeks of the simulation, which could be the result of other dynamics not consider in this study for the sake of simplification, such as voting dynamics and promotion programs of the website. Despite this minor bias in our simulation, the results project the overall behavior of users in the case study.

4.2.3 Asymmetric communities

So far, we have simulated a symmetric community where user opinions are distributed normally with a mean of zero on two dimensions of U_1 and U_2 (see Fig. 1). However, online communities could be asymmetric, i.e., biased. The popularity of a community within specific groups of users with specific mindsets, subsets of initial users who invite and attract like-minded individuals to join the community, among other reasons, could form a community that is biased toward one quadrant of the opinion space; see Fig. 1 for the descriptions of each quadrant. Here, we study the effect of community bias on user activity rates and the evolution of the community.

It should be noted that we studied communities biased toward supporting or opposing the Iranian government and being fans of yellow or green stories. The overall dynamics of simulation outcomes were similar for both. We focus our presentation of results on being supportive/against the government, a dimension that is both more coherent and somewhat more interesting. Furthermore, given the nature of political polarities, extremeness often develops in social media. We therefore analyze such extreme behaviors as well in the following two sub-sections.

4.2.4 Politically biased communities

We changed the mean of users' opinion in the first dimension (i.e., $u_{Opinion\,1}$ which represents U_1 in Fig. 1) in the range of $[-1, 1]$ (from users mostly opposing the Iranian government to mostly supporting the government) with a step size of 0.1, and ran a simulation with 500 users for each step size, a total of 21 simulated data series of 500 users. We assume all other model variables stay the same and no new users joining the system, so that the changes in simulation results can be described by the changes in the initial means of users' opinion.

Interestingly, the simulation results for total weekly posts indicate that more asymmetric communities ($\mu = 1.0, 0.9, -1.0, -0.9$, highlighted as blue for supporters and red for opponents of the Iranian government in Fig. 5a) post more stories compared to less asymmetric and symmetric ones ($\mu = 0.0, -0.1, 0.1$, highlighted as purple). Communities opposing the Iranian government generally post more stories compared to those supporting the government. However, compared to well-mixed communities, more uniform communities, regardless of their opinions, ultimately post more stories.

Moreover, results show that communities biased toward opposition or support of the government generate more comments ($\mu = 1.0, 0.9, -1.0, -0.9$ highlighted in Fig. 5b with blue and red lines) compared to symmetric communities ($\mu = 0.0, 0.1, -0.1$ highlighted in purple). Ultimately, all lines in Fig. 5 converge to zero as revisit rates go down to zero.

4.2.5 Extremeness in supporting or opposing the Iranian government

We also studied the effect of having more extreme opinions (toward the Iranian government) on the formation of the communities, by changing the standard deviation of users' opinion in the first dimension (i.e., $u_{Opinion\,1}$) in the range of $[0.1, 2.0)$ (from less biased to extreme supporter/opponent of the Iranian government), with 0.1 step size change in the standard deviation.

The result shows that total published stories present a faster decrease (shown as blue lines in Fig. 6a) in posts over the long haul when users are more extreme in their opinions. The change in average weekly posts is not significant in this case (see Online Supplementary Materials, Fig. S6), which implies that the behavior is mainly driven by the change in the online rate. The average online rate (see Online Supplementary Materials, Fig. S7) also indicates that in all groups, users tend to visit the community less often when the community's opinion is more extreme. This is due to the fact that the online rates (in all groups of opinions) decrease when users interact with stories contrary to their point of view (e.g., when Users-II read Stories-III), since β_6, β_7, β_{10} and β_{11} are estimated to be positive in the revisiting regression. When communities are more extreme, the effect of these coefficients increases and, as a result, online rates decay faster. This could mean that users remain in communities for a shorter time where there are active individuals with opinions extremely different from their own.

Total published comments follow the same pattern, in which users have more discussion in less biased communities (Fig. 6b). Based on the coefficient estimated for changes in comment rates, users tend to have more discussions when they read stories with opposing opinions (β_6, β_7 and β_{10} are negative). However, more comments are published as a result of users contributing to discussions in response to their published posts. Thus, posting more stories in less biased communities encourages users to discuss more.

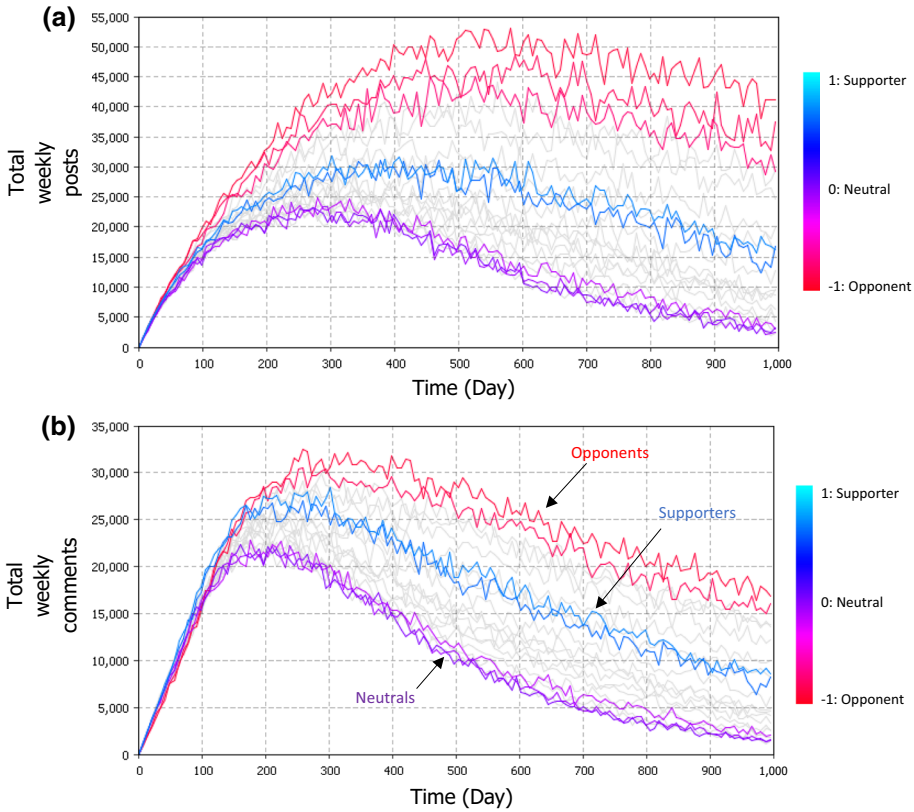

Fig. 5 **a** Total weekly posts, and **b** total weekly comments; for communities with different bias levels over 1000 days −1.0 and 1.0 bias levels represent complete bias against and in favor of the Iranian government, respectively. Zero bias level represents neutral. *Red lines* show the opponents and *blue lines* show the supporters. For the sake of presentation, *eight lines* are highlighted that show extremely biased, minimally biased, or neutral communities. (Color figure online)

4.2.6 Attractiveness of stories

Finally, we changed the mean of stories' attractiveness ($s_{Attractiveness}$) in the range of [−1.0, 1.0] (from less attractive to more attractive) with a step size change of 0.1. This analysis on the attractiveness of stories highlights that total published posts and comments are higher in communities with more attractive stories (Fig. 7a, b). Posting rates are not sensitive to stories' attractiveness (see Online Supplementary Materials, Fig. S8); however, high changes in online rates are observed (see Online Supplementary Materials, Fig. S9). This implies that reading more attractive stories will not necessarily encourage users to post more, but will lead them to visit the website more often.

Interestingly, in the case of Users-I and Users-IV, more attractive stories (with μ close to one, see Online Supplementary Materials, Fig. S9) can even increase the online rate, persuading those users to return to the website more frequently and breaking the overall pattern of activity decline. Comment rates, however, are highly sensitive to the attractiveness of stories (see Online Supplementary Materials, Fig. S10) and increase for more attractive

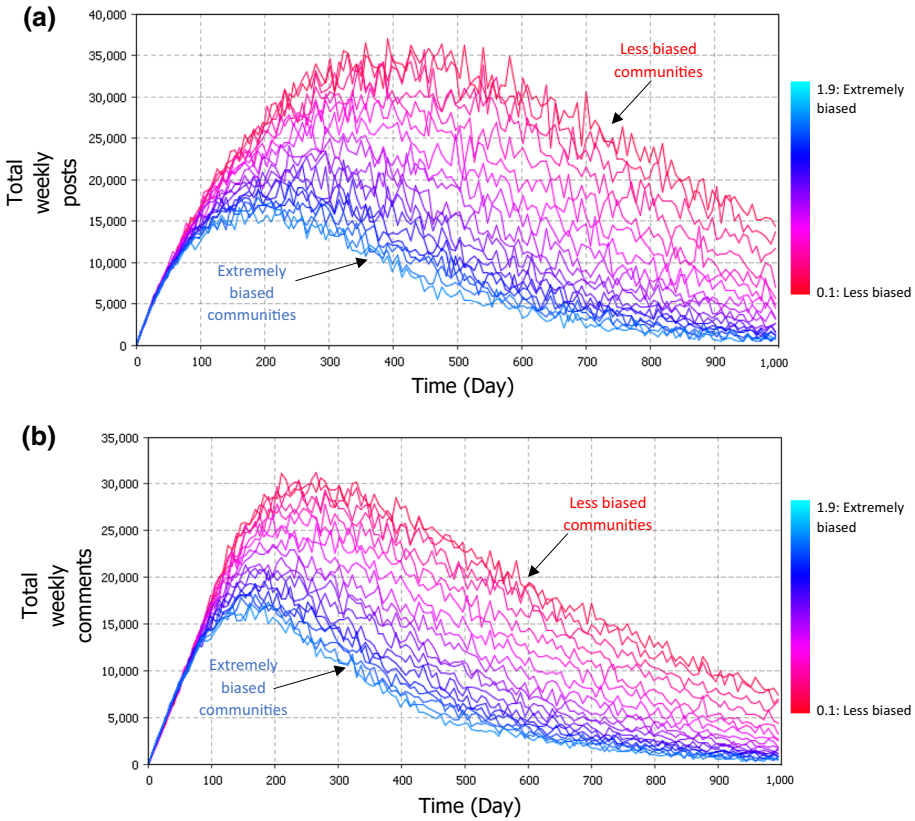

Fig. 6 **a** Total weekly posts, and **b** total weekly comments; for communities with wider bias levels over 1000 days. *Red lines* represent less biased communities and *blue lines* represent more extremely biased communities. (Color figure online)

stories across all groups. Therefore, all users tend to discuss attractive stories more, regardless of their opinions.

5 Discussion and conclusions

The importance of online social media platforms in people's daily life is well recognized. Individuals use social media to stay in touch with their family and friends, share ideas (Bakshy et al. 2012), and spread the word about petitions (Jalali et al. 2016), services or products (Trusov et al. 2009; Tucker 2014), just to name a few. Overall, we now spend around 7%-10% of our lives on social media.[12] Social media is also used as internal communication tools in organizations, and can also help increase internal engagement among employees and generate new ideas across teams (Gose 2013; Wadee 2013). But the growing pattern masks much rise and fall among various platforms. What explains those ebbs and flows?

In this research, we studied the effect of individual interaction with a variety of opinions in social media on online activities, and consequently on the formation and future of platforms. Considering that users have a critical role in the life cycle of social media, where they are

[12] GWI Social report 2015: A typical internet user on average spend 1.77 hours per day on social networks, while younger generations spend more than that (2.68 h for 16–24 years old and 2.16 for 25–34 years old).

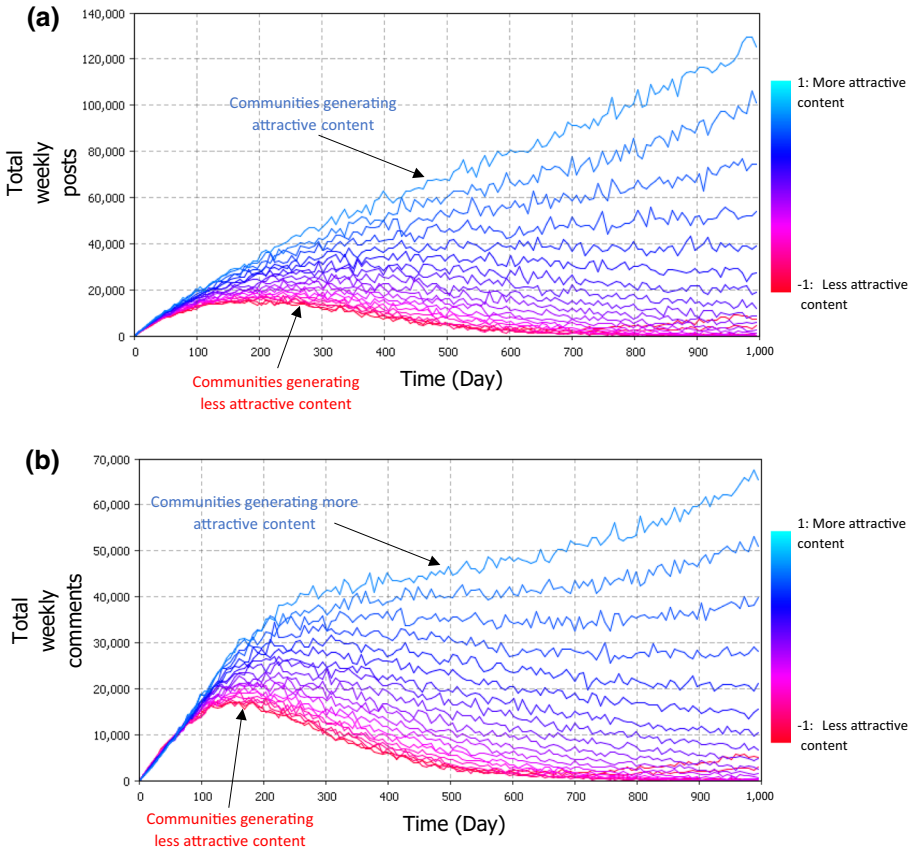

Fig. 7 **a** Total weekly posts, and **b** total weekly comments; for communities generating more/less attractive content over 1000 days. *Red lines* present the results for communities generating less attractive content and *blue lines* present the results for communities generating more attractive content. (Color figure online)

content generators, we focused on user behaviors. We estimated different mechanisms that influence individual behaviors, and studied the effect of these mechanisms on the life cycle of social media through an agent-based simulation model. We then examined the effect of different compositions of users on individual activity and the future of social media. Although our data extraction algorithm, opinion estimation method, and models for changes in user activities (as the three main components of this research) were customized for the types of data we collected from a particular case study platform, all of these components are relatively generic and similar models can be tailored and applied to other social media platforms.

Our results indicate that individuals' reactions to each other's opinions vary based on the content and tone of the online objects. While there are variations in reactions, depending on where the individual stands on these factors, we found that, individuals increase their activity on social media upon interacting with content that closely matches their own opinions; moreover, encountering extreme content could have a negative effect on individual activity levels. Furthermore, the attractiveness of the content (i.e., the attractiveness of the stories independent of content and tone) plays an essential role in keeping individuals interested and active on the outlet. That is likely a reason why many social media platforms focus on promoting the more liked content.

Besides exploring the impact of consumed opinions on user activities, some practical implications follow from our results. First, it seems that keeping users entails engaging them with content that is closely aligned to their opinions (i.e., by creating clusters of like-minded users and feeding them with content generated among themselves). Most of the social network platforms today use recommendations and ranking algorithms that work based on the proximity of opinions. Some extract users' opinions directly (using methods such as collaborative filtering) and feed the users content that has proven interesting to other like-minded people (e.g., Netflix and Pandora recommend movies and songs to users based on the taste of other users), while others use different proxies to feed users content closely aligned to their own opinions (e.g., Facebook feeds its users content shared by their friends or pages in which they are interested). Both cases create plurality in communities, which, based on our results, increases the life cycle of outlets. Yet, ranking algorithms in both cases treat all of the opinion groups the same, which may not be optimal. There is no difference in the ranking of opponents' stories for supporters and supporters' stories for opponents, although they may react differently to opposing opinions. Our study, however, shows that different opinion groups could be treated according to their overall reactions, in order to maximize user activity rates.

A more fundamental challenge to society relates to the impact of these filtering algorithms on users' opinions, which we did not discuss here. If, consistent with the goal of maximizing user retention and activity, users are shown content in sync with their opinions, they may find few opportunities to be challenged and revise their opinions. Such filter bubbles may hurt democratic conversations that are critical to sifting through complex social problems, building understanding across ideological gaps, and solving big challenges that require people of different opinions to come together. To the extent that social media companies are forced to create filter bubbles to thrive, the society may be facing a prisoner's dilemma situation in which no firm dares to promote cross-boundary communication, which is in everybody's interest. There is much interesting research to be done in this space, bridging firm-level profit considerations and societal goals.

This study is subject to several limitations. The data is limited to the particular case under study and readers should be cautious about the generalizability of the results. Our regression and simulation results also mostly reflect correlations in empirical data rather than causation. We estimate opinions based on voting patterns, and while attractive due to scalability, this method misses on direct measurement of opinions which would be more reliable. Furthermore, our simulation study is fairly simple in that it does not consider many relevant feedback mechanisms and exogenous effects and only explores the results of the mechanisms we empirically identify. Future research could benefit from using larger datasets and data from different types of social media platforms. They could also attempt at identifying the causes of the mechanisms discussed in this study, and incorporate more feedback loops. Studying the effects of voting dynamics and promotion systems, which are often used in social media, could be other areas for extending this work.

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