Do you really like me? A communication pattern for polarized Internet discussion forums

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Abstract

We propose a general schema for analyzing the interactions between communities on Internet forums. Initially, the interactions on three Internet political forums are measured examining a relevant set of observable variables, which include the number of likes, the length and depth of the conversations, etc. Then, we present a statistically significant structural equation model which combines these observable variables into only three latent variables. In all the forums the factors of the observable variables related to *like* have a contrary sign to the factors describing the length and depth of the debate. Thus, we conclude that showing agreement with like is different, and in fact opposite, to starting and developing a debate. These results are potentially relevant to the current debate about the extent to which digital social networks generate negative effects on political communication and would allow the researchers to compare the characteristics of different forums.

1 Introduction

There is a general agreement on the fact that the extension and social use of social networks has a measurable effect on the form and characteristics of communication, and in particular of political communication [1, 2]. However, there is no such broad agreement on the direction of this effect. In this sense, exist empirical studies that show how the exchange of information and political opinions through Internet discussion forums and social networks helps to strengthen relations between citizens and between them and public representatives [3]. For this to occur, it is necessary that users of forums and social networks have a willingness to establish strong communication links. That is, do not just express agreement or disagreement (for example, with the "like" option offered by many digital tools), but establish conversations with a certain degree of depth. Likewise, the exchange of open and inclusive information is considered relevant. The recurrence of these circumstances is interpreted as a positive effect of political communication mediated by digital devices over democracy [4].

However, other studies point at the risks associated with this type of communication. Among these, special emphasis has been placed on the political polarization that digital social networks can generate [5] and, as an expression of this polarization, the use of inappropriate expressions or incivility [6]. One of the undesired effects of digital social networks is their capacity to favor the selection of the interlocutor. Thus, while off-line interaction facilitates the exchange information with people about whom we do not know their political identity, ideology or points of view on controversial issues, digital social networks allow us to select in which space we want to participate and what are the ideological characteristics of this space, as well as that of its participants. This capacity for "hyperselection" reduces the randomness of political interaction, fosters homophily and, potentially, polarization [7]. Finally, in highly polarized contexts the likelihood of the use of negative or insulting expressions increases,

Variable	Informal Description
likesCom	number of *likes* received from the own community
likesOther	number of *likes* received from other communities
debatesCom	number of debates established with users of the same community
debatesOther	number of debates established with users of other communities
depthDebatesCom	depth (length) of the debates established with users of the same community
depthDebatesOther	depth (length) of the debates established with users of other communities
badWords	use of incivil or bad words from part of the user

Table 1: List of observed variables for each user

which not only imply a lack of courtesy or respect but are, in many cases, an attempt to exclude the other from the conversation [8].

Our general objective is to deepen this debate. To do this, we start with three case studies in which, given the subject of debate and the context in which they occur, the risk of extreme opposing political positions, that is, potentially polarized and therefore uncivilized, is high. These issues are: the position and belonging of Catalonia to the Spanish state in the online forum of the newspaper *La Vanguardia*, the departure of Great Britain from the European Union in the online forum of the newspaper *The Sun*, and the political debate between democrats and republicans in the United States of America in *The politics forum*.

The interaction between users in these forums is usually expressed in three ways:

1. Posting a new message, that is starting a *conversation*.
2. Answering to an existing message.
3. Use the *like* feature on some existing message to show agreement.

Although some Internet forums also include the possibility of showing *dislike*, this feature is not available in all of them, and we have chosen the minimal setting described above.

Given all the messages of a certain forum in a certain period of time, and provided that we have determined previously to which community belongs each user, we propose to measure the interactions of each user in the forum calculating the observed variables of Table 1. Although the description of these variables is informal[1], the overall idea is enough to establish our hypotheses:

H_1 *Communication pattern hypothesis.* The variables of Table 1 can give raise to a structural equation model with only three latent variables: *In*, that describes the relation of the user with her same community, *Out* that describes the relation of the user with the rest of the communities, and *InOut*, that expresses the tension between the own and the other communities. Moreover, this model is statistically significant for the three Internet forums examined.

H_2 *Like-debate tension hypothesis.* Debating and giving *like* are opposite ways of interaction, independently if we are interaction with the own community or with another community.

H_3 *Depth of the debate hypothesis.* Focusing on the debates, the participants tend not to get involved in a wide range of issues. However, when they are involved in a topic, their participation is intense. As in H_2, this holds independently if we are interacting with the own community or with other communities.

Methodologically, we check the hypothesis by fulfilling these two goals:

G_1 *Community detection goal.* The first step is to assign a community to each user. We have developed an algorithm based on the idea of *affinity ratio* between two users, which roughly

[1] See Section 3.3 for a precise definition of each observed variable

A *I think that....* - liked by: A,D,C

  D *@A however,....*

    A *@D ...*

  B *@A you are wrong...*

    C *@B what @A means is...* - liked by: A

      B *@C I understood @A's point. But...* - liked by:E

    A *@B no, you miss that...* - liked by: C

      B *@A, as I explained to @C...* - liked by: E

Figure 1: An example of conversation in an online forum. The name of the user that posts the message is the first letter, which is colored according to the community the user belongs to

corresponds to the number of *likes* between both of them. This yields a weighted graph, where the users are the nodes and the affinity ratio the weight. Then, we use a standard community detection method based on the concept of *modularity* [9].

G_2 *Confirmatory analysis goal.* In order to check that the observed variables correspond to the latent variables *In*, *Out* and *InOut* (hypothesis H_1) we employ confirmatory analysis and check if the corresponding indices indicate that the relation is statistically relevant.

G_3 *Analysis of the loadings.* The goal here is to obtain the associated coefficients or *loadings* of the observed variables in the latent variable for our three examples to check the hypotheses H_2 and H_3. In particular, H_2 holds if in our three forums the coefficients related to *like*, that is *likesCom* and *likesOther*, have a different sign than the variables related to the debate, *debatesCom*, *debatesOther*, *depthDebatesCom*, and *depthDebatesOther* both for the *In* and the *Out* latent variables. Hypothesis H_3 holds if we found that the loadings of *depthDebatesCom* (respectectively *depthDebatesOther*), which indicate the depth of the debate, are greater than the loadings of *debatesCom* (respectively *debatesOther*) which measure the number of debates the user gets involved in.

The article is organized as follows. Goal G1 is developed in Section 2, which also specifies the characteristics of the three forums used as a case study. Goal G2 is carried out in Section 3, which also defines formally the observed variables. Section 4 analyzes the results of the confirmatory analysis (goal G3). Finally, Section 5 contains the conclusions of the study, in which we argue about which of the two hypotheses is verified.

2 Community Detection

In our framework we assume a polarized context, that is, the users can be classified according to their different stances. Thus, our first goal is to detect these *communities* and assign each user to one of them.

Our notion of community is based on the number of *likes*: we assume that when some user shows agreement with the opinions of another one, it is very likely that both users share similar points of view, and hence that they belong to the same community. This idea is formalized defining an *affinity ratio* for each pair of users. Then, we apply an off-the-shelf community detection algorithm that splits the users into communities taking into the account the affinity ratio.

Before presenting these concepts, we introduce the characteristics of the forums analyzed and the three datasets studied in this paper.

	La Vanguardia	The Sun	The Politics Forums
URL	www.lavanguardia.com/politica	thesun.co.uk/news/politics	thepoliticsforums.com
Country	Spain	United Kingdom	USA
Period	Oct-Nov 2018	Jul-Nov 2018	Jan-Nov 2018
Users	3042	1641	235
Topics	1485	1119	3079
Conversations	163813	27436	3050
Messages	523547	60760	43019

Table 2: Summary description of the three datasets

2.1 Online Social forums

We consider online social forums where the user can choose between the three forms of interaction described in the first section:

- Post a new message creating a new *conversation*. In Figure 1, the user A has created a new conversation by posting a new message, represented as the root of a tree (the different colors of the user names correspond to the communities, as explained below).
- Reply to some message of an existing conversation. In Figure 1 users D and B reply to the initial message of A.
- A user can *like* any message, expressing agreement. For instance, in the figure, the initial message has been liked by users A, D and C.

Morever, we assume that in their messages, the users can *mention* other users. In our example we have used the notation '@username'. By default, we assume that the replies to some message include at the beginning a mention to the replied user. This is not a requirement, but a common practice in online forums.

The replies can split the conversation in several branches as depicted in Figure 1. For instance, the three first messages A-D-A form a branch, while A-B-C-B is another branch, and A-B-A-B is the third branch of the conversation.

We are especially interested in conversations that include debates in some of their branches. Formally, we define a *debate* as an interaction between two users A and B of the form A-*-B-*-A-*-B, where * represents 0 or more intermediate messages.

The idea is that just one reply cannot be considered a debate, and thus we have defined as debate a branch in a conversation with at least two messages of each user, a structure that we think is more likely to represent a minimum interchange of ideas.

2.2 Datasets

We have chosen three online political forums from different countries, all of them containing the features indicated above.

The three datasets are:

- *La Vanguardia*: the online news forum associated to the news about politics of the most read newspaper in Catalonia (Spain) [10].
- *The Sun*: the integrated forum of the most read newspaper in English [11].
- *The Politics Forums*: an online forum created in 2012 and dedicated to political issues, either debating about USA, worldwide or other countries.

A brief description of the dataset can be found in Table 2. The row *topics* indicates the number of news about politics considered in the case of *La Vanguardia* and *The Sun*, and to the number of threads in the subforum *US Politics in General* of *The Politics Forum*.

2.3 Affinity Ratio

We measure the affinity between two users, u_1, u_2 as the ratio of two values as explained by Algorithm 1. In this algorithm, the local variable l computes the number of conversations

Algorithm 1: Affinity ratio algorithm

```
Input  : A dataset D, users u1, u2
Output: affinity(u1, u2)
l = 0;
m = 0;
for conversation c in D do
    if u1 likes at least one message of u2 in c then
        l++;
    else
        if u2 mentions u1 but u1 does not like at least one message of u2 in c then
            m++;
        end
    end
end
if m+l==0 then
    affinity(u1, u2) = 0;
else
    affinity(u1, u2) = l/(m+l);
end
```

that contain a like from u_1 to u_2, while the local variable m counts those conversations with a mention of u_1 from part of u_2 that do not include a like from u_1 to u_2. The idea is that mentions are direct interpellations that are usually corresponded with a 'like' representing an agreement or even a salutation if both users are from the same community. Thus, the ratio penalizes those mentions that are not corresponded by a like, considering them a lost opportunity to show agreement. However, missing such mentions are not so important if there are many likes from u_1 to u_2. Thus:

- $\mathit{affinity}(u_1, u_2) = 0$ indicates that there is no like from u_1 to u_2.
- $\mathit{affinity}(u_1, u_2) > 0$ but small indicates that there are many mentions to u_1 from u_2, but also that these mentions are usually not corresponded by like, which corresponds to a small degree of affinity.
- $\mathit{affinity}(u_1, u_2) > 0$ and near one indicates that either the mentions are corresponded by like or at least that there are many likes from part of u_1 to u_2.

With this information, we build a weighted directed graph G, where the nodes represent the users, and there is an edge with weight $w > 0$ between two users u_1, u_2 if $\mathit{affinity}(u_1, u_2) = w$.

2.4 Modularity-based community detection

In the last few years have been an extensive research on the field of community detection [12] in particular on social networks [13] [14], focusing in many occasions on the interactions between the users [15] [16]. Among the most successful algorithms are those based on the concept of *modularity*, that looks for partitions of a network into communities of densely connected nodes, with the nodes belonging to different communities being only sparsely

(a) La Vanguardia (b) The Sun (c) The Politics Forum

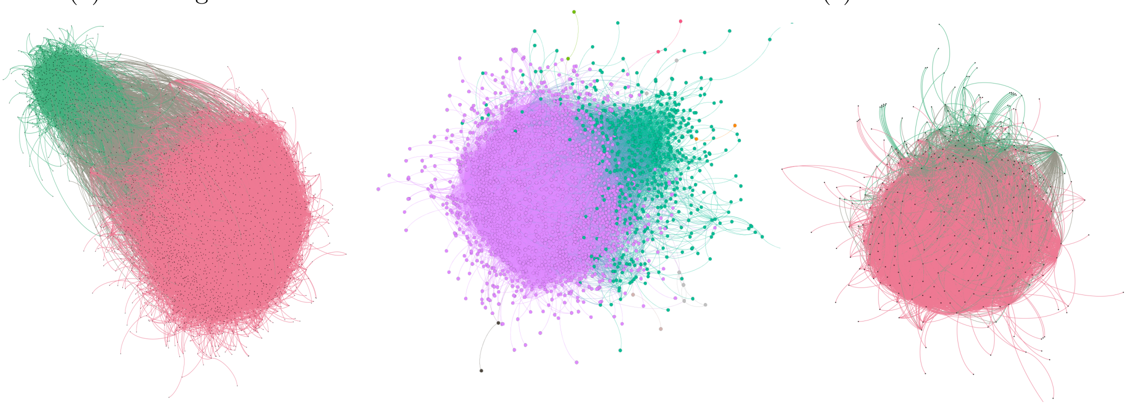

Figure 2: Detected communities visualized by Gephi

connected [17]. In particular, we have used the modularity algorithm included in the software Gephi [18], using the *affinity ratio* algorithm to quantify the affinity between users.[2]

In the three datasets we have found that there are two main communities, which can be described as follows

- *La Vanguardia*: the two communities correspond to users in favor (30%) and against (70%) the independence of Catalonia. The period analyzed correspond to the first anniversary of the independence referendum, and the debates focus on this subject almost regardless of the news of the day.
- *The Sun*: the users are divided between in favor (73%) and against (26%) of Brexit. Again, this is related to the analyzed period that corresponds to the debate about the Brexit agreement between United Kingdom and the European Union. About a 1% of the users was not classified in either of the two groups. Figure 2b shows the communities according to Gephi.
- *The Politics Forums*: the users are split into republicans (79%) and democrats (21%). This is worst-balanced division, as Figure 2c shows.

The previous labels for each community are just our appreciations observing the messages of each community members. However, and in order to somehow validate the result in the case of *La Vanguardia*, we post a message in the forum asking the users about which community (pro-independence or against independence) the would assign to the top 100 most active users. This test was tried twice in different periods of the day to get feedback from different users. The response was very positive, and the 100 users were classified, almost with no discussion. The result was only one (in the first test) or two (second test) disagreements between the forum users and our algorithm on the community of the 100 most active users.

3 An Online Forums Model based on confirmatory analysis

As result of the previous Section, we can assume that each user belongs to some community that has been already determined. In this section, we present the model used to characterize

[2]A caveat of this implementation is that it does not allow directed graphs. Instead, given two users u_1 and u_2 it sums the weights of the two edges between them, given rise to an undirected weighted graph. We have found that this simplification works well in practice.

polarized forums. The proposed model is defined by three latent variables. The first one, which we call *In*, represents the relation of each user with its own community, the second variable, *Out*, corresponds to the interaction of each user with other communities, and, finally, *InOut* expresses the tension between the previous variables.

3.1 Structural Equation Modeling

Since these variables cannot be directly observed due to their abstract character, we need a technique that can:

- Derive the values of *In*, *Out* and *InOut* from other variables directly observed.
- Ensure that the model is statistically significant given the particular dataset, that is, that the *latent* variables are really defined by the *observed* variables.

These two properties are accomplished by *structural equation modeling* [19] (SEM) a multivariate model in which each equation represents a causal link, rather than a mere empirical association between two variables. SEM has been described as a combination of exploratory factor analysis and multiple regression [20]. In particular, in this paper we consider *covariance-based* SEM, a technique used to confirm/reject the model depending on how well it can estimate the covariance matrix of the sample data set.

A structural equation model usually consists of two main components, a structural model and several measurement models. A simple measurement model includes a latent variable, a few associated observed variables and their corresponding measurement errors. The structural model contains all latent variables and their interrelationships [21].

Before showing our proposed model, we need to introduce some useful auxiliary definitions.

3.2 Auxiliary Definitions

In the rest of the paper we employ the following notation:

- $\mathcal{D}$ represents the dataset.
- $\mathcal{C}$ contains all the conversations in $\mathcal{D}$. We use $c \in \mathcal{C}$ to denote the particular conversations.
- $\mathcal{B}(c)$ is the set of branches that occur in a conversation c. We use $b \in \mathcal{B}(c)$ to denote a particular branch of the conversation c.
- $\mathcal{U}$ the set of users in $\mathcal{D}$.
- $\mathcal{C}(u)$ are those conversations in which the user $u \in \mathcal{U}$ has participated, that is

$$\mathcal{C}(u) = \{c \in \mathcal{C} \mid u \in \mathcal{U} \textit{ such that } u \textit{ participates in } c\}$$

- $com(u)$ the set of users that are in the same community as u.
- $likes(v, u, c)$ the user v likes some message of u in the conversation c.
- $debates(u, v, b)$, when the users u and v have a debate in a branch b. We also speak about $debates(u, v, c)$ when exists some branch $b \in \mathcal{B}(c)$ such that $debates(u, v, b)$.
- $length(b)$ the number of messages in a branch.

As usual, the notation $|S|$ represents the number of elements of a set S.

3.3 The observed variables

The observed variables are measured directly from the forum analysis. In particular, we attach seven values to each user, each one corresponding to an observed variable. Next, we list the arbitrary names and the description of each variable.

- *likesCom(u)*. The ratio between the number of conversations in which a user participates and other user from the same community gives him at least a like, among the number of total conversations in which he participates. More formally:

$$likesCom(u) : \frac{|\{c \mid c \in \mathcal{C}(u) \ such\ that\ for\ some\ \ v \in \mathcal{U}, v \in com(u), likes(v,u,c)\}|}{|\mathcal{C}(u)|}$$

- *likesOther*: Analogously to the previous variable, but the like is given by a user from a different community:

$$likesOther(u) : \frac{|\{c \mid c \in \mathcal{C}(u) \ such\ that\ for\ some\ \ v \in \mathcal{U}, v \notin com(u), likes(v,u,c)\}|}{|\mathcal{C}(u)|}$$

- *debatesCom*: The ratio between the number of conversation in which a user get into *debate* with other or others user from the same community, among the user total of conversations.

$$debatesCom(u) : \frac{|\{c \mid c \in \mathcal{C}(u) \ such\ that\ for\ some\ \ v \in \mathcal{U}, v \in com(u), debates(u,v,c)\}|}{|\mathcal{C}(u)|}$$

- *debatesOther*: Equivalent to *debatesCom* but measuring the debates with user from a different community.

$$debatesOther(u) : \frac{|\{c \mid c \in \mathcal{C}(u) \ such\ that\ for\ some\ \ v \in \mathcal{U}, v \notin com(u), debates(u,v,c)\}|}{|\mathcal{C}(u)|}$$

- *depthDebatesCom(u)*: This variable evaluates the average number of exchanged messages in the debates of the user with users from the same community. Formally,

  $Define\ S = |\{b|b \in \mathcal{B}(c) \mid c \in \mathcal{C}(u) \ such\ that\ for\ some\ \ v \in \mathcal{U}, v \in com(u), debates(u,v,b)\}|$

  Then:

$$depthDebatesCom(u) : \frac{\sum_{b \in S} length(b)}{|S|}$$

- *depthDebatesOther(u)*: Like *depthDebatesOther* but measuring the lenght of the user's debates with other communities users.

  $Define\ S = |\{b|b \in \mathcal{B}(c) \ \mid c \in \mathcal{C}(u) \ such\ that\ for\ some\ \ v \in \mathcal{U}, v \notin com(u), debates(u,v,b)\}|$

  Then:

$$depthDebatesOther(u) : \frac{\sum_{b \in S} length(b)}{|S|}$$

- *badWords(u)*: This variable quantifies how polite is a user, measuring in how many of his conversations she uses incivil or bad words from the user total of conversations.

$$badWords(u) : \frac{|\{c \mid c \in \mathcal{C}(u) \ such\ that\ u\ included\ a\ bad\ word\ in\ some\ message\ in\ c\}|}{|\mathcal{C}(u)|}$$

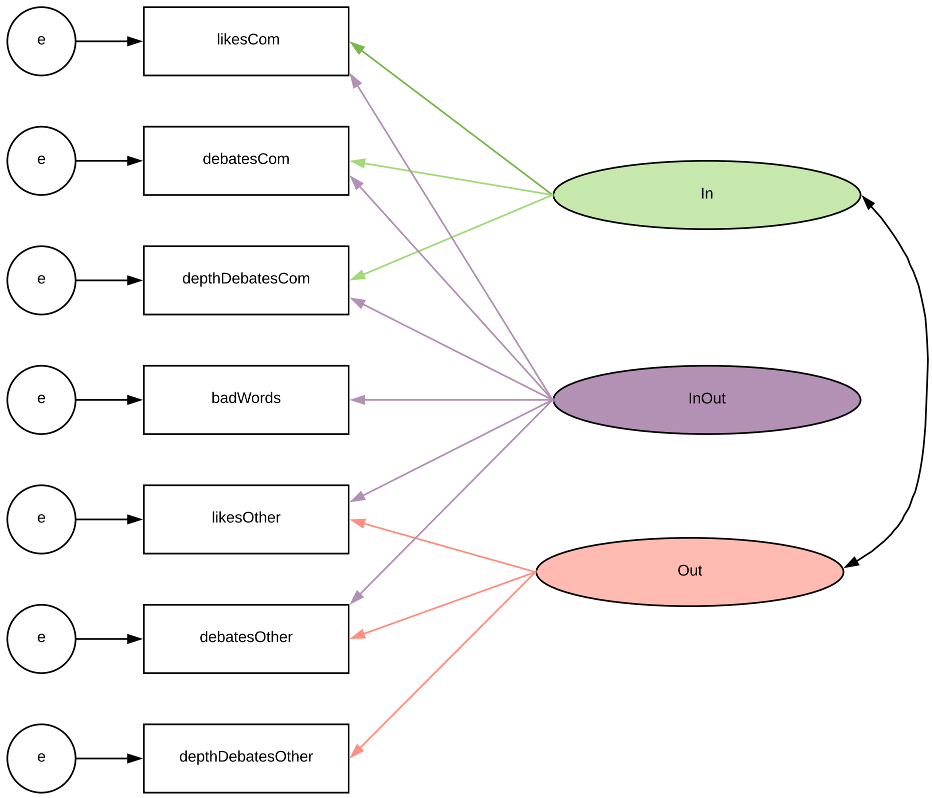

Figure 3: Proposed Model: latent variables are displayed in ellipses and observed variables in boxes

3.4 The Model

Then, we elaborated several plausible models and use *SEM* to check if any of them provide a statistically significant model of the observed variables in term of a reduced number of *latent* or *hidden* variables.

The aim of this search was to find out whether the variables used in our study could be employed to measure the different aspects of political communication. This type of analysis also allows us to know which of this broad set of variables are statistically significant to, in this way, take them as a basis for the interpretation of the phenomenon studied.

It is worth mentioning that we started the research with a set of 19 observed variables, including many variables not described in the previous section (such as the number of conversations initiated, number of messages using upper letters, number of users of the other community mentioned by unit of time, etc.), but we could not find any significant model including all of them.

Thus, after discarding many models and variables because the statistical indexes proved that they did not fit the data (see next subsection), we came out with the SEM model of Figure 3. The model is represented by a directed digraph, the so-called *path model*. Path models include traditionally five elements [22]: *latent variables*, represented by ellipses (in our diagram, *In*,*Out* and *InOut*), the *observed* (also called *measured* or *constructed*) variables, depicted as rectangles, their *error terms* represented as circles, the *relationships between the latent variables and their respective observed variables*, represented by an arrow, and *correlations* between latent variables, represented by double arrows.

For instance, in our diagram, we can see that the latent variable *In* is defined by the observed variables that explain the relationship between each user and her community: *likesCom*, *debatesCom*, and *depthDebatesCom*. Analogously, it can be observed that the

	La Vanguardia	The Sun	The Politics Forums
Degrees of fredom (DF)	8	8	8
Dataset size	3042	1641	235
RMSEA	0.02262177	0.008713607	0.05444354
RMSEA 90% CI	(0.010634, 0.03499634)	(NA, 0.0310773)	(NA, 0.1029388)
SRMR	0.0131118	0.01301759	0.03859246
Bentler-Bonett NFI	0.9954303	0.9946425	0.967407
Tucker-Lewis NNFI	0.9926628	0.998423	0.9630968
Bentler CFI	0.9972049	0.9993992	0.9859416

Table 3: Statistical adjustment of the three datasets: degrees of freedom, dataset size, and several common fit indices

latent variable *Out* is defined by those variables that express the relationship of a user with the users of the rest of the communities. Finally, the latent variable *InOut* depends on all the observed variable, except for *depthDebatesOther*. The reason for not including this variable is that *depthDebatesOther* and *depthDebatesCom* have a statistical correlation of 0.76 in the case of the dataset of *La Vanguardia*, 0.56 in *The Sun* dataset, and of 0.78 in *The Politics Forum*. In the diagram, we can also observe that we have included a correlation between *In* and *Out* latent variables.

3.5 Statistical significance of the model

The table 3 presents several indices that allow us to estimate the fitness of the model [23]. The indices check the ability of our model to reproduce the data and have been obtained using the *sem* library of the R language [24].

Since we have 7 observed variables, we have a covariance matrix with $7 \times 8/2 = 28$ different values. We must estimate 20 parameters: 12 *loadings* (the factors associated to the arrows), one correlation factor (the double arrow), plus 7 errors. This results in a model with 28-20 = 8 degrees of freedom. The number of degrees of freedom combined with the size of the dataset is important to assess the confidence of some indexes such as the RMSEA [25]. Next, we examine the goodness of each fit index.

RMSEA. The *Root Mean Square Error of Approximation* (RMSEA) is currently the most popular measure of model fit. In [26] the values 0.01, 0.05, and 0.08 to indicate excellent, good, and mediocre fit, respectively. In our case, the three datasets report excellent or good fit. However, in the case of *The Politics Forum* the confidence interval extends to 0.10, which is the usual cutoff. Thus, we could say that according the model is suitable according to this index, although with some doubts in the third dataset.

SRMR. The *Standardized Root Mean Square Residual* (SRMR), is the standardized difference between the observed correlation and the predicted correlation, and a value under 0.08 is considered a good fit [27], which happens in our three datasets.

NFI. The *Normed Fit Index* (NFI), also known as *Bentler-Bonett Index* [28] is an incremental measure of fit. A vale 0.95 is considered good fit, and this occurs in our three datasets.

NNFI or *TLI*: The *Non-normed Fit Index*, also known as *Tucker Lewis Index* [29] improves the previous index by adding a penalty when more parameters are added. Again our three datasets verify that the value is above 0.95.

CFI. The *Comparative Fit Index* [30] is an incremental measure similar to the TLI and it is usually required to have a value over 0.9.

It is worth noticing that we have included neither the chi-squared indexes since they are no longer relied upon as a basis for acceptance or rejection [31], nor the AIC, BIC indexes which are used to compare models and not to assess the goodness of fitting. Notice that

Latent Var.	Factor	La Vanguardia	The Sun	The Politics Forum
In	In_likesCom	-0.1100659459	-0.1452053639	-0.014360301
	In_debatesCom	0.0261191826	0.0147330842	0.042161373
	In_depthDebatesCom	0.0590659212	0.1896904878	0.27769129
Out	Out_likesOther	-0.0177132342	-0.0247105929	-0.002522077
	Out_debatesOther	0.0460938979	0.0495617239	0.035095462
	Out_depthDebatesOther	0.0620874489	0.1748431725	0.279348633
InOut	InOut_badWords	-0.0021776912	-0.0003585812	0.003082573
	InOut_depthDebatesCom	-0.017034371	-0.0865674425	-0.014193483
	InOut_likesOther	0.001930673	0.0167422426	-0.050637955
	InOut_likesCom	-0.1999791713	-0.2494381836	-0.134402795
	InOut_debatesOther	0.0188761925	0.0159585568	0.102164256
	InOut_debatesCom	-0.0010273261	-0.002577238	0.085669377
	ρ	0.6489820711	0.4261925306	0.537415859

Table 4: Loadings of the three datasets

the use of three different datasets is also useful to disregard the problem of *capitalization of chance* [32]. Finally, it must be mentioned that even small changes in the model lead to non-significant indexes. The data, the models and the scripts in R to check them can be found at *suppressed to ensure anonymity, available from the editor*

Summarizing, we can say that our model fits well the data, and thus the latent variables *In*, *Out* and *InOut* can be considered a suitable representation of the underlying structure of the observed variables, as expressed in our hypothesis H_1. It is worth mentioning that even small changes in the model (adding or replacing a correlation or a dependency between a latent variable and an observed variable) yields a non-fitting model.

4 The confirmatory model as a communication pattern

In this section we analyze the model and the composition of latent variables in terms of the observed variables.

4.1 Interpreting the latent variables

In order to interpret the model, we need to check the observed variable that affect each latent variable and their particular loadings (also called factors) that connect latent and observed variables. Each loading corresponds to an unidirectional arrow between a latent and a an observed variable in the figure 3, and is represented in the table 4 with a name of the form *latent_Observed*.

In Figure 3, we observe that the first latent variable (*In*) informs us about the internal communication of the own community, since it only depends on the variables *likesCom*, *debatesCom*, and *depthDebatesCom*.

Analogously, *Out* only depends on those observer variables that reflect the relation with the other communities, that is, *likesOther*, *debatesOther*, and *depthDebatesOther*.

The factor loadings of each observed variable in each latent variable, and for the three datasets, can be found in Table 4. The loadings are prefixed by the name of the latent variable, followed by the name of the observed variable. For instance, *In_likesCom* is the factor that must be applied to the observed variable *likesCom* in the latent variable *In*.

In the case of *In* and *Out* we observe the same tendency, which corresponds to hypothesis H_2: in both latent variables, and in the three cases, the number of likes has a different sign than the variables related to the debates. This indicates that pressing like is complementary, and in fact opposite, to debating. Moreover, comparing the two variables related to the debates, the factor for *depthDebatesCom*, *depthDebatesOther* have greater weight than the factors associated to *debatesCom*, *debatesOther* (hypothesis H_3).

The third variable, *InOut*, represents the tension between the strategies of both communities; *In* and *Out*. That is, the strategy that rewards communication with members of the same community and the strategy of openness to communication with other communities. In the three forums the loading with greater weight is the *likesCom* variable, representing the approval of the own community. In the cases of the newspaper's forums, the loadings of this variable dominates clearly the rest of loadings, indicating that this "self-approval" is the most important factor. However, in the case of *The Politics Forum*, the likes of the own community are reinforced by the likes of the other community and have a sign contrary to the number of debated with both the own and the other communities. Thus, in this forum and for the *InOut* variable we can say that there is a tension between the number of likes in general and the number of conversations, which constitutes a difference with respect to the case of the *In* and *Out* variables.

5 Conclusions

The results of this research help us to meet the proposed objectives, as well as to verify our hypotheses.

Regarding G_1, devoted to community detection, we have defined an affinity ratio, which is one of the contributions of the paper, and allow us to create a weighted graph that can be analyzed with standard techniques to detect to different communities involved in the discussion. Considering the three particular cases studied here, we have shown that, although there are majority and minority positions, the result in all cases are two clearly positioned communities. That is, we are facing three cases of study in which the positions of both parties are well defined.

The goal G_2 was to obtain a structural equation model which can be validated with respect to the three cases of use. This model is presented in Figure 3, which represents another contribution of this paper. The fit indexes of Table 3 confirm that the model can be applied to our three cases, which allows us to propose this model as a communication pattern (hypothesis H_1).

With respect to the goal G_3, obtaining and analyzing the loadings for the three cases of study, the values obtained confirm hypothesis H_2, because the loadings of the observable variables associated to *like* in the latent variables *In* and *Out* (see Table 4) have a sign contrary to the loadings of the observed variables associated to the debate. In this sense, it seems that using the *like* feature is opposed to opting for a more elaborate debate. This is confirmed when we observe the weight of the variables *depthDebatesCom* and *depthDebatesOther*, which explain the recurrence of debates conceived based on a deep exchange of points of view. Given this result and taking up issues that we raised in the introduction, we can say that the debates in which there is a clear attempt to develop the ideas that each of the parties defends have a significant value in these forums. This is particularly noticeable regarding the variable *depthDebatesOther* because it indicates that participants have a high interest in discussing elaborately with people who are not part of their community. That is, although the circumstances were conducive to polarization (controversial subject and complex sociopolitical context), participants do not engage and debate only with the people of their community, but are open to in-depth debate with others.

It is worth observing that our results resemble the hypothesis proposed for Twitter in the paper *"Measuring user influence in twitter: The million follower fallacy"* [33], which states that having a great number of followers in twitter do not imply to have a great influence. On the contrary the influence seems to be achieved getting involved in the conversations often in specific themes. Both works (this paper and [33]) compare an easy and immediate sign of approval (following someone in the case of Twitter, giving *likes* in our case) with the more complicated task of getting involved in conversations and debates. In both cases the result is that the two mechanisms constitute a different, and in fact opposite, way of interacting in the social media.

In this same direction, and comparing in particular the loadings of *debatesCom* and *depthDebatesOther* in the latent variables *In* and *Out*, we observe that the depth of the debates has a greater impact than the numbers of debates. That is, the participants in the three debates tend not to get involved in a wide range of issues arising in the context of the debate they are in, but when they are involved in a topic, their participation is intense. This result reinforces the thesis of the communicative commitment of the participants in these debates.

Finally, we found that incivility samples are very scarce. It is a behavior that does not respond to what is expected in polarized contexts [7]. Thus, we can consider that these are communicative processes that, despite the tension inherent to the political circumstances in which they occur, do not generate high levels of intransigence and disqualifications among the participants.

It is important to emphasize that we are not saying here that, because of this study, we can generalize the hypotheses, but that these results suppose a further proof [3] that supports this point of view. It is the sum of case studies like this that will allow us to assume as definitive the hypothesis of democratic deepening. However, given the current state of this line of research, this is still difficult to affirm.

There are some issues that should be mentioned before closing this section. The first, that this study takes three cases in which the debates take place outside the most used social networks (Twitter, Facebook, YouTube, etc.). We assume that this can have a regulating effect of the debate in the sense of moderating the opinions and feelings of the participants. These are smaller and more restricted forums in which the participants are, speculatively, people with greater interest in politics. Secondly, it is a context of non-electoral debate and, therefore, not co-opted by media and political leaders. This, as has been shown in several studies [34] has an important effect on political polarization since they are precisely the most active accounts in social networks (presumably media, political parties, etc.) those that establish a more polarized and extreme debate. Not having in this work the participation, at least intensively, of these communicative profiles, can have a substantive effect on the characteristics of the debate. Our results confirm that at least in the cases studied, there is a significant disposition to exchange opinions with members of other communities (not polarization), as well as a reduced presence of uncivil expressions.

An obvious future work is to obtain more data from other forums and check if the same communication pattern holds. Moreover, it would be very interesting to observe the evolution of the loadings for the same forum but in different periods of time, checking for instance the depth of the debates increases or if, on the contrary, is the like feature which tends to dominate. A different line of research would be try to explain better the meaning of the three latent variables, and in particular of *InOut*, which we have not used in our hypotheses.

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