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Targets of Online Hate Speech in Context. A Comparative Digital Social Science Analysis of Comments on Public Facebook Pages from Romania and Hungary

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Abstract[1]

Online hate speech, especially on social media platforms, is the subject of both policy and political debate in Europe and globally – from the fragmentation of network publics to echo chambers and bubble phenomena, from networked outrage to networked populism, from trolls and bullies to propaganda and non-linear cyberwarfare. Both researchers and Facebook Community Standards see the identification of the potential targets of hateful or antagonistic speech as key to classifying and distinguishing the latter from arguments that represent political viewpoints protected by freedom of expression rights. This research is an exploratory analysis of mentions of targets of hate speech in comments in the context of 106 public Facebook pages in Romanian and Hungarian from January 2015 to December 2017. A total of 1.8 million comments were collected through API interrogation and analyzed using a text-mining niche-dictionaries approach and co-occurrence analysis to reveal connections to events on the media and political agenda and discursive patterns. Findings indicate that in both countries the most prominent targets mentioned are connected to current events on the political and media agenda, that targets are most frequently mentioned in contexts created by politicians and news media, and that discursive patterns in both countries involve the proliferation of similar stereotypes about certain target groups.

Keywords: Social Media; Hate Speech; Romania; Hungary; Digital Social Science; Text Mining.

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1. Introduction

As digital communication becomes a bigger part of our lives and both the real and virtual world become increasingly globalized and diverse, new issues such as studying online hate speech make their way onto the scientific and policy agenda. With new networked digital platforms, collapsed public, semi-public, and private contexts and a wealth of data in public online conversations, digital social science methodologies are increasingly adopting computational approaches.

In the international and European socio-political context, associated with economic migrants, refugees and increasing waves of extremism and xenophobia, hate speech is becoming an increasingly important topic. Where the fundamental human right to freedom of speech and expression collides with the increasing need for tolerance and mutual respect demanded by life in racially, ethnically, and religiously diverse, multicultural societies, hate speech becomes an important preoccupation for researchers, law-makers, civil society and stake-holders in public-mediated communication.

The issue of online hate speech has risen in importance in global and European debate over the past few years. Although European laws regulate hate-speech acts, computer-mediated communication through digital platforms owned by businesses outside users' countries may be subject to different legislation. At the heart of the most heated debate is the social media giant, Facebook, whose platform is used by approximately 2.2 billion people globally. Governments and NGOs look to this company to create mechanisms that properly deal with antagonistic speech, in accordance with national policies. The case of Germany, a country with one of the strictest regulatory frameworks in Europe concerning antagonistic speech, is well known. Against the backdrop of the European refugee crisis, Facebook was pressured to take action and announce an initiative to deal with racist content on its German website.[2] In early 2016, the company reacted to public criticism over its reluctance to deal with hate speech within EU and European national legal frameworks by outsourcing the moderation of racist posts.[3] At the end of 2016, social media activity and social or political effects associated with the former had driven lawmakers in both Europe and the United States to further increase pressure on Facebook to '*clamp down on hate speech, fake news and other misinformation shared online, or face new laws, fines or other legal actions.'*[4]

Romania and Hungary provide interesting cases for comparative research on the issue of online hate speech in Central and Eastern Europe for several reasons. As neighboring countries, the two share history and culture, and throughout the past century the two modern national states have had conflicting territorial claims.

[2] Donahue, P. (2015) Merkel Confronts Facebook's Zuckerberg Over Policing Hate Posts. *Bloomberg.com*, 26 September. Available at: https://www.bloomberg.com/news/articles/2015-09-26/merkel-confronts-facebook-s-zuckerberg-over-policing-hate-posts . Accessed: 06-01-2018.

[3] Auchard, E. (ed.) and ten Wolde, H. (2016) Facebook Outsources Fight Against Racist Posts in Germany. *Reuters*, 15 January. http://www.reuters.com/article/facebook-germany-idUSKCN0UT1GM . Accessed: 06-01-2018.

[4] Scott, M. and Eddy, M. (2016) Facebook Runs Up Against German Hate Speech Laws. *The New York Times*, 28 November. Available at: http://www.nytimes.com/2016/11/28/technology/facebook-germany-hate-speech-fake-news.html . Accessed: 06-01-2018.

Transylvania, a region of Romania since 1918, is inhabited by a substantial Hungarian minority. The two countries also share the recent common experience of communist regimes and propaganda until 1989, both being part of the bloc behind the Iron Curtain. The two languages are significantly different – Romanian is an Eastern Romance language, while Hungarian is a Finno-Ugric language – and are hence well suited for an exploration of differences in methodological approaches to studying the linguistic aspects of hate speech. Last, recent social and political developments in the two countries – from the use of Facebook in relation to political debate and participation, the use of social media by media institutions, alternative media and activism groups, and the content of media and political agendas – drive research interest in a comparative approach. Comparative research traditionally aims to highlight differences between cases worth comparing, such as the situations in our two countries. However, similarities are also sometimes interesting as they may be indicative of trends and phenomena that transcend the national context or linguistic boundaries. Whether hate speech has such components that extend beyond the obviously context-specific ones is an issue central to our paper and worth investigating further.

2. Approaches to Studying Hate Speech

A 2015 UNESCO study (Gagliardone et al., 2015) outlines the key issues relevant to countering online hate speech:

Definition: There are multiple, differing definitions of hate speech, some mixing concrete threats to the security of individuals and groups with expressions of frustration and anger. Digital media communication platforms such as Facebook, Twitter and Google each define their own policies towards admissible content published by their users. However, as recent tensions have shown, these often clash with national legislation, and consensus seems unlikely.

Jurisdiction: Online networked communication platforms have given private spaces of expression a public function and the combined speed and reach of internet communication raise new issues for governments trying to enforce national legislation in the virtual public sphere, often in contexts managed by companies located in other states.

Comprehension: There seems to be a lack of comprehension about the relation between online hate speech phenomena and offline speech and action or, more precisely, violent action. In Gagliardone et al. (2015) the authors highlight the lack of studies that examine the links between hate speech online and other social phenomena.

Intervention: Different contexts for online communication have given birth to different intervention strategies – from user flagging, reporting or ranking to monitoring, editorializing and counter-speaking. However, popular online social-network-type platforms seem reluctant to publish aggregate results that would allow an overview of the phenomenon.

The academic approach towards studying hate speech defines the phenomenon as an act of communication. An overview of the issue in the Romanian national context (Angi and Bădescu, 2014) recommends focusing on: content (what is being said); emitters (who is communicating); targets (who the message is about); and context (including when the act takes place).

A similar point is made in the context of Hungarian legal case studies by Peter Smuk, who argues that hate speech, understood as speech that incites hatred against persons or social groups, can be defined in terms of 'actors (orators), the contents, targets (victims) and social dangers posed' (Smuk, 2015: 64).

For the purposes of this research, the main focus will be studying the mentions of targets, defined here as vulnerable groups in each national case (as identified by previous scientific literature) and the context – virtual space, temporal coordinates and conversational themes.

2.1 Defining Hate Speech

For the purposes of this research, the definition of hate speech is the most important issue. According to Gagliardone et al. (2015: 19), '[the] ICCPR [International Covenant on Civil and Political Rights] is the legal instrument most commonly referred to in debates on hate speech and its regulation, although it does not explicitly use the term.' The problem of defining hate speech has been approached by researchers in various fields. In the case of online hate speech, the issue is particularly linked to jurisdiction – although there seems to be a consensus that it targets disadvantaged social groups in potentially harmful ways. Definitions exist in different national contexts but may differ substantially from each other and those used by social media platforms in their content policies and community guidelines.

Although Facebook has been under criticism since 2015 for not blocking some content, especially by institutions and policy groups in the EU, the company released its Community Standards on April 24, 2018,[5] stating that its policy rationale for blocking hate speech is because it 'creates an environment of intimidation and exclusion and in some cases may promote real-world violence.' Its choice of definitions and approach were discussed as early as June 2017.[6]

Facebook defines hate speech with respect to 'protected characteristics':

> We define hate speech as a direct attack on people based on what we call protected characteristics – race, ethnicity, national origin, religious affiliation, sexual orientation, caste, sex, gender, gender identity, and serious disease or disability. We also provide some protections for immigration status. We define attack as violent or dehumanizing speech, statements of inferiority, or calls for exclusion or segregation.[7]

[5] Constine, J. (2018) Facebook Reveals 25 Pages of Takedown Rules for Hate Speech and More. *TechChrunch*, 24 April. Available at: https://techcrunch.com/2018/04/24/facebook-content-rules/ . Accessed: 13-10-2018.

[6] Allen, R. (2017) Hard Questions: Who Should Decide What Is Hate Speech in an Online Global Community?. *Facebook Newsroom*, 27 June. https://newsroom.fb.com/news/2017/06/hard-questions-hate-speech/ . Accessed: 10-06-2018.

[7] *Community Standards*. Facebook. Available at: https://www.facebook.com/communitystandards/hate_speech . Accessed: 13-10-2018.

The categories of hate speech are defined under three tiers and a supplementary category:

> Tier 1 attacks, which target a person or group of people who share one of the above-listed characteristics or immigration status [...]
> Tier 2 attacks, which target a person or group of people who share any of the above-listed characteristics [...]
> Tier 3 attacks, which are calls to exclude or segregate a person or group of people based on the above-listed characteristics. We do allow criticism of immigration policies and arguments for restricting those policies.
> Content that describes or negatively targets people with slurs, where slurs are defined as words commonly used as insulting labels for the above-listed characteristics.[8]

The company's policy explicitly mentions that the above criteria apply to both verbal and visual content, and also defines special cases of admissibility such as raising awareness, education, self-referentiality, empowering expressions, humor and social commentary with clearly identifiable intent.

2.2 Studies of Online Hate Speech in Central, Southern and Eastern Europe

Although still relatively scarce, scholarship on online hate speech in Central and Eastern Europe has been emerging at a fast pace in the past decade from both academics and NGOs.

An overview of the issue mentioned above (Angi and Bădescu, 2014) finds that the most frequent targets of hate speech in the Romanian national context are the Roma, Hungarians and Jews, and members of the LGBTQ+ sexual minorities. Similarly, in Hungary, the most frequently targeted groups are reported to be the Roma, Jews, the LGBTQ+ community, and, in recent years, refugees and migrants (Article 19, 2018: 8). In Hungary, the very definitions of hate speech or incitement to hatred have also been the topic of highly politicized debates, an overview of which is beyond the scope of this paper (see: Boromisza-Habashi, 2011; Pál, 2015).

The NGO sector has taken increasing interest over the past two years in analyzing and developing strategies for countering hate speech in the traditional and online media. Reports and academic work emanating from these initiatives are starting to shape the emerging scholarship on the issue (Răileanu et al., 2016; Hann and Róna, 2017).

Existing academic research and the numerous reports from the NGO sector focus mainly on legislation, media self-regulation and intervention strategies, while the actual content of hate speech acts in the online media, especially in social media, are the subject of analysis mostly through case study methodology, potentially leading to hasty generalizations and the overlooking of some targets, contexts or emitters. The issue of hate speech in the Central and Eastern European context has been approached mostly from a regulatory or normative perspective in relation to Western

[8] *Community Standards*. Facebook. Available at: https://www.facebook.com/communitystandards/hate_speech . Accessed: 13-10-2018.

Europe and the United States in comparative studies (Heinze, 2013). However, it is only very recently that academic researchers have started investigating the niche topic of online hate speech by making use of computational approaches in the collection and analysis of large datasets of comments from news web sites, blogs, and especially social media (Meza, 2016).

Other recent multi-country initiatives have investigated the issue of online hate speech in the Southeastern European region in countries such as Albania, Bosnia and Herzegovina, Kosovo, Macedonia, Montenegro, Serbia and Turkey, following international standards related to raising issues such as the broader socio-historical context of the expression, the identity and intent of the speaker, the content of expressions, and the magnitude of distribution and likelihood of ensuing discrimination.[9]

A report on hate speech against Jewish and Roma groups on social media proposes an analysis of types of antisemitism using the following dominant categories: religion, racism, conspiracy, economy, anti-Israeli, demonizing.[10] For the analysis of the stereotypes associated with the Roma community, the authors appeal to different categories such as: inferior race, criminals, uneducated/uncivilized, demographic threat, cultural threat, social welfare recipients, prejudicial to the image of Romania. In Hungary, sociological research into antisemitic attitudes, although not directly involving an investigation of online discourses, also points to the importance of the online environment in the rise of antisemitism after 2010, as this appears to enable the spread of conspiracy theories and misinformation in an age of post-truth (Hann and Róna, 2017: 38).

3. Networked Agendas – The media, politicians, and the networked public

Over the last 50 years agenda setting has evolved from an initial focus on media effects on the public's perception of the most important issues to a more complex, hierarchical approach to understanding the effects of communication.

News media transmit the salience of relationships between sets of objects and attributes to the public. These sets of relationships between elements of the media and public agendas are the third level of agenda-setting (Guo, 2014). This perspective on the bundling of agenda elements – the third level of agenda-setting – tests an agenda-setting hypothesis that the salience of relationships on the agenda of media networks can be transferred to the public network issue agenda (McCombs et al., 2014).

The Network Agenda Setting Model borrows concepts from the associative network model of memory and asserts that individuals' cognitive representation of

[9] Lani, R. (ed.) (2014) *Hate Speech in Online media in South East Europe*. Tirana: Albanian Media Institute. Available at: http://www.institutemedia.org/Documents/PDF/Hate%20speech%20in%20online%20media%20in%20SEE.pdf . Accessed: 10-06-2018.

[10] 'Elie Wiesel' National Institute for the Study of the Holocaust in Romania (2016) *Raport cu Privire la Discursul Instigator la Ură Împotriva Evreilor şi Romilor în Social Media (English: Report on Hate Speech against Jews and Roma in Social Media)*. Report. Bucharest: Institutul Naţional pentru Studierea Holocaustului din România 'Elie Wiesel'. Available at: http://www.inshr-ew.ro/ro/files/proiecte/DIU/DIU_social_media_1.pdf . Accessed: 10-10-2018.

objects and attributes may be thought of as a network-like structure, where any particular node will be connected to numerous other nodes. This recent theoretical approach asserts that in order to describe an individual a person generates a network-shaped picture composed of various attributes which are connected to each other in their mind (Guo et al., 2012).

In the context of this research, beyond identifying and quantifying the mentions of targets of hate speech in comments on Facebook posts by news media, political leaders and political parties, an analysis of co-occurrence networks between such mentions, negative qualifiers, and institutions connected to recurrent themes in society may reveal directions for further exploration. Beyond the target groups identified by researchers who previously studied hate speech in the Romanian and Hungarian national contexts, the present research tries to identify mentions of social groups such as refugees, welfare recipients and pensioners who were salient in the media and political agenda in the two countries within the timeframe of the analysis.

4. Terms in Context and Co-occurrence Analysis

Although text mining and natural language processing tools are increasingly being used by social scientists to study digital documents, there is still a considerable gap between the tools available for international languages such as English, French, Spanish, Italian and German and languages which are spoken only in national contexts such as Hungarian or Romanian. Although in past years resources for languages such as Romanian and Hungarian have been increasingly made available, and newer approaches based on machine-learning applied to large enough corpora are ever more language independent, social investigations into online hate speech in the two national contexts have mostly applied traditional qualitative and quantitative methods of analysis.

The exploratory approach presented here is based on researcher-defined niche dictionaries (of targets/vulnerable groups, issues/concepts/institutions and qualifiers defined as semantic families) and descriptive statistics in relation to contextual variables (Facebook page source and category, time frame of the comment thread). Furthermore, the research uses semi-automated coding based on the above-mentioned niche dictionaries (for targets and issues/concepts) to map co-occurrences between the two categories. This approach allows for the identification of contexts where antagonistic speech has the potential to appear. Large-scale research studies such as this require more advanced natural language processing tools (and machine learning techniques) for Hungarian and Romanian that can automatically classify content. It is worth noting that even Facebook relies on the decision-making ability of over 7,000 content moderators to classify and potentially block such content from the platform.

Co-occurrence analysis is used to identify relations between the target groups and social institutions, issue concepts or qualifiers related to stereotypes (based on semantic families). This method combines quantitative content analysis approaches (code/term frequencies) with network analysis (relations based on the co-occurrence of terms/codes in the same context – e.g. in the same comment) (Danowski, 1993). The merits of the method are particularly notable when analyzing content produced in computer-mediated communication, especially in the case of short text messages/documents such as user comments where the significance of two terms co-occurring in the same text is greater. Furthermore, by applying network analysis methods groups of well-connected terms or concepts may be detected using algorithms for community structure detection in graphs (Clauset et al., 2004). As edges are defined based on the co-occurrence of a relationship (two terms or coded concepts appear in the same message), edges connecting separate (or loosely connected) parts of the graph will have high betweenness scores (they will frequently be found on the shortest path connecting those parts of the graph). A hierarchy of well-connected modules can be established by identifying edges with high betweenness scores, eliminating them, and then reiterating multiple times. As a result, communities will emerge as dense, well-connected groups of nodes, or in this case terms or concepts coded from the comments corpus. This approach may reveal latent connections.

5. Method

As Facebook's definition focuses on the 'protected characteristics' that define several categories of target groups, it becomes important to identify and analyze the incidence of mentions of categories qualified as vulnerable groups by the platform's policy guidelines and previous research in the Romanian and Hungarian national context.

The goal of the research is to identify the vulnerable groups that are most frequently mentioned in Facebook comments to posts on public pages owned by politicians, political groups and media in the two countries.

This exploratory research is guided by the following research questions:

RQ1: Which are the most frequently mentioned targets (vulnerable groups)?

RQ2: What are the contexts (community, temporal, discursive) in which mentions of targets (vulnerable groups) appear frequently?

RQ3: How do Romanian and Hungarian Facebook Pages compare in terms of frequency of mentions of targets (vulnerable groups) and contexts for such mentions?

5.1 Data Collection and Sampling

Some of the most recent research into the issue of online hate speech has improved on previous approaches in terms of adopting sampling strategies that are a better fit for social media and defining a more nuanced conceptual framework by distinguishing between three categories of antagonistic speech: dangerous speech, hate speech, and offensive speech (Gagliardone et al., 2016). The cited study uses purposeful sampling as a preliminary step to identifying patterns in online hate speech. This research takes a similarly purposeful sampling approach in this exploratory comparative study with respect to the two cultural, linguistic, social and political contexts – Romania and Hungary.

This analysis is based on a total of 106 public Facebook Pages (55 from Romania and 51 from Hungary). The sample of pages was selected purposefully to include the most prominent, popular and relevant news media, online communities, political parties and political leaders. For both countries, the sample includes all the pages of the parliamentary parties and their leaders, the news media with the largest

Facebook audience, the largest online communities focused on entertainment, as well as alternative media pages and political activist communities. The Romanian sample also includes two entries for the most prominent satirical online news outlets. Audience sizes were evaluated using socialbakers.com and facebrands.ro, services which retrieve and update Facebook page audience data.

Data was gathered through Facebook Open Graph API (Application Programming Interface) interrogation using the Facepager tool (Keyling and Jünger, 2013). The time frame for the analysis was three years – from 1 January 2015 to 31 December 2017. Table 1 lists the categories of pages and the number included in the sample for each language. The pages of The Democratic Union of Hungarians in Romania and its leader Hunor Kelemen were included in the Romanian sample, but due to the fact that both the page messages and comment messages are in both Romanian and Hungarian, it was only analyzed in the preliminary steps of the analysis.

Table 1. Sample Facebook Page categories

Romanian sample		Hungarian sample	
News media	11 pages	News media	12 pages
Online Community	14 pages	Online Community	16 pages
Political Party	7 pages	Political Party	9 pages
Political Leaders	19 pages	Political leaders	14 pages
Satire	2 pages		
The Democratic Union of Hungarians in Romania	2 pages		
Total	55 pages	Total	51 pages

A total of 1,880,750 comments were collected from 144,396 public posts. The distribution of comments in the two languages is 1,031,866 comments from Romanian pages and 848,884 comments from Hungarian pages.

The 1.88 million comments were filtered using two niche dictionaries which contained multiple forms of the terms used to refer to the targets of hate speech identified as vulnerable groups by the literature on the subject in the two national contexts. As comments are moderated by Facebook content reviewers, some comments that did not abide by the platforms' community standards had been deleted and, as a result, were impossible to collect. However, it is only in the past year and a half that the company has made a considerable effort to increase the number of content reviewers thus the review process will most likely be triggered by user reporting and focus more on new comment threads. Even though the latency of the research topic may be high (with no exact way of measuring it), detecting mentions of target groups may still be relevant when identifying threads that served as a context for hate speech, even if most of the comments which contained hate speech have been removed.

Table 2. Target groups used as filters in two niche dictionaries

Roma/Gipsy	Hungarian and Romanian dictionary
Hungarian/Romanian	Romanian dictionary/Hungarian dictionary
Transylvanian	Hungarian and Romanian dictionary
Szekler	Hungarian and Romanian dictionary
Jewish	Hungarian and Romanian dictionary
Muslim	Hungarian and Romanian dictionary
Religious	Hungarian and Romanian dictionary
Atheists	Hungarian and Romanian dictionary
LGBT	Hungarian and Romanian dictionary
Refugee/migrants	Hungarian and Romanian dictionary
Poor/welfare recipients	Hungarian and Romanian dictionary
Pensioners	Hungarian and Romanian dictionary
Hungarians outside borders	Hungarian dictionary

Table 2 lists the groups that were considered. Most groups were included in both dictionaries. Hungarians were included only in the Romanian dictionary, whereas Romanians were included only in the Hungarian dictionary. Terms and phrases referring to '*Hungarians outside borders'* were included only in the Hungarian language dictionary. In all cases, the stems for the most common terms (including explicitly offensive terms) referring to each target group were included in each dictionary.

The categories sex and gender, as featured in definitions of protected characteristics for potential targets of hate speech, were not included due to linguistic characteristics that make it difficult to detect such targets through keyword filtering. For example, in Romanian, the use of grammatical gender allows reference to women without explicitly using any noun from the semantic family of the word 'woman'. However, as explained in a previous section, groups such as welfare recipients, pensioners and refugees/migrants were included due to their prominence in the media and political discourse in the time frame of the analysis, even though they are not on Facebook's list of protected groups.

The results of the filtering process revealed that 25,912 (2.51 per cent) of the total comments for Romania contained terms referencing target groups and 26,026 (3.06 per cent) of total comments in Hungary contained terms referencing target groups.

Previous research on hate speech in online comments on Facebook in the Romanian national context (Meza, 2016) shows that although mentions of target groups are usually found in around two per cent of comments, in less than half of these comments (below one per cent) these terms co-occur with negative qualifiers, obscenities, etcetera.

Primary descriptive statistics were generated using Tableau software. Co-occurrence networks were generated using KH Coder (Higuchi, 2001) to show the conversational context for mentions of the target groups in the comments posted on Facebook. The two niche dictionaries used for filtering comments based on references to target groups were supplemented with additional definitions for concepts based on semantic families (containing semantically related terms referring to social institutions, frequently featured on the media and public agendas, and qualifiers often employed in group stereotypes). Codes based on semantic families were defined for concepts such as: *Church, religious holidays, religion, money, corporations, business, government, education, political parties, EU, sex and sexuality, alcohol, theft, stupidity, laziness, violence*. The coded concepts allow the exploration of the dataset for associations with key institutions/organizations in society and for stereotypical representations of social groups.

This approach aims to explore connections between target groups and the media and political agendas in Facebook user comments under the Networked Agenda Setting framework, as well as the prevalence of negative stereotypes in a comparative perspective.

6. Findings

The analysis of mentions of target groups in the Romanian language sample (Figure 1) reveals that the most frequently mentioned category is welfare recipients, followed by the Roma and Hungarian groups. The largest number of mentions was detected in comments posted on the pages of political leaders and news media outlets. There are also significant mentions of other categories such as Muslims, refugees/migrants, pensioners and sexual minorities.

Comments containing references to target groups (RO)

	Facebook Page Categories				
Targets (RO)	News Media	Online Communities	Political Parties	Politicians	Satire
Null	98,03%	98,58%	98,15%	95,93%	97,56%
welfare/poor	0,50%	0,26%	0,53%	0,85%	0,36%
Roma/Gipsy	0,50%	0,16%	0,14%	0,38%	0,50%
Hungarian	0,19%	0,18%	0,30%	0,64%	0,46%
Muslim	0,24%	0,18%	0,14%	0,50%	0,17%
refugees/migrants	0,15%	0,07%	0,16%	0,48%	0,09%
LGBT	0,11%	0,10%	0,09%	0,43%	0,21%
pensioners	0,13%	0,03%	0,35%	0,38%	0,30%
religious	0,05%	0,20%	0,02%	0,12%	0,07%
Jew	0,05%	0,12%	0,04%	0,13%	0,05%
Transylvanian	0,02%	0,05%	0,05%	0,06%	0,13%
atheists	0,01%	0,05%	0,01%	0,07%	0,03%
Szekler	0,02%	0,01%	0,02%	0,04%	0,06%

Figure 1. Mentions of target groups in comments in Romanian

In the Hungarian sample (Figure 2), mentions of refugees and migrants are by far the most frequent, followed, as in the Romanian sample, by mentions of the Roma. Mentions of Muslims, pensioners and Jews are also significant.

Comments containing references to target groups (HU)

	Facebook Page Categories			
Targets (HU)	News Media	Online Communities	Political Parties	Politicians
Null	97,39%	99,23%	95,48%	95,74%
refugees/migrants	1,29%	0,19%	2,58%	2,05%
Roma/Gipsy	0,34%	0,11%	0,44%	0,61%
Muslim	0,33%	0,05%	0,42%	0,46%
pensioners	0,13%	0,04%	0,43%	0,39%
Jew	0,17%	0,06%	0,24%	0,26%
LGBT	0,19%	0,20%	0,12%	0,17%
welfare/poor	0,08%	0,03%	0,17%	0,15%
Szekler	0,05%	0,06%	0,05%	0,07%
Transylvanian	0,03%	0,02%	0,06%	0,07%
atheists	0,01%	0,01%	0,01%	0,02%
Romanian	0,00%	0,00%	0,01%	0,01%
religious	0,00%	0,00%	0,00%	0,00%
Hungarian outside borders	0,00%		0,00%	

Figure 2. Mentions of target groups in comments in Hungarian

In both cases, the largest number of mentions of target groups appears in the context of political leaders' Facebook pages, reflecting a connection between the public communication of politicians and user conversations revolving around topics that include groups often targeted by antagonistic speech. However, the second largest number of conversations mentioning these groups are found on the pages of Romanian news outlets, while in the Hungarian case the second most numerous mentions of target groups are found on the pages of political parties (closely following the number of mentions on politicians' pages) to provide a context for such conversations, while news media outlets generate fewer mentions.

Another interesting result is the difference in the incidence of mentions of Hungarians in the Romanian sample (the third most frequently mentioned target group) and the incidence of mentions of Romanians in the Hungarian sample (11^{th} position). References to Transylvanians or *Hungarians outside borders* are also not amongst the most prominent terms.

Analysis of mentions by time distribution reveals that in the Romanian sample mentions of welfare recipients peaked in the fourth quarter of 2016. This coincides with the Romanian Parliamentary elections in which the Social Democrat Party gained 45 per cent of the seats after a campaign based on a program that promised prosperity and higher pay for several social groups, including state employees and pensioners. Some of the oppositional discourse attributed the result of the elections to the mobilization of pensioners and welfare recipients from the poorer regions of the countries. Figure 3 also shows peaks for the mention of refugees in the third quarter of 2015 and the first quarter of 2016, coinciding with the peak of the European refugee crisis and its aftermath. Mentions of other prominent target groups in the corpus (Roma, Hungarians) show little fluctuation over the time frame analyzed. References to Muslims coincide with the peaks for refugees/migrants, but also peak during the fourth quarter of 2016 – which may be explained by the Social Democrats' initial controversial proposal of Sevil Shhaideh (a Muslim) for Prime Minister of Romania in December 2016. Many of the mentions of target groups peak in the last part of 2016, which may be due to electoral campaigning.

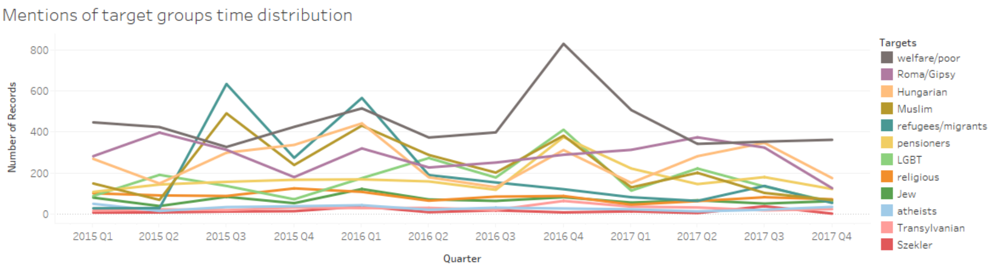

Figure 3. Mentions of target groups in the Romanian sample by time frame quarter

The time distribution of mentions of target groups in the Hungarian corpus in Figure 4 shows references to refugees and migrants peaking in the third quarter of 2015 (the height of the European refugee crisis) and in the third quarter of 2016, when European countries were dealing with a second wave of refugees. No significant fluctuations for other target groups appear over time. It is worth noting, however, that similarly to the Romanian case, the peaks for mentions of Muslims match the peaks for the mentions of refugees/migrants. Whereas in the Romanian corpus mentions of refugees/migrants decrease significantly by the beginning of 2017 to well below those for other target groups, in the case of the Hungarian corpus these mentions remain the most frequent by far even at the end of the period of analysis (Quarter 4 of 2017), indicating that topics related to refugees and migrants were still on the news media and political agenda.

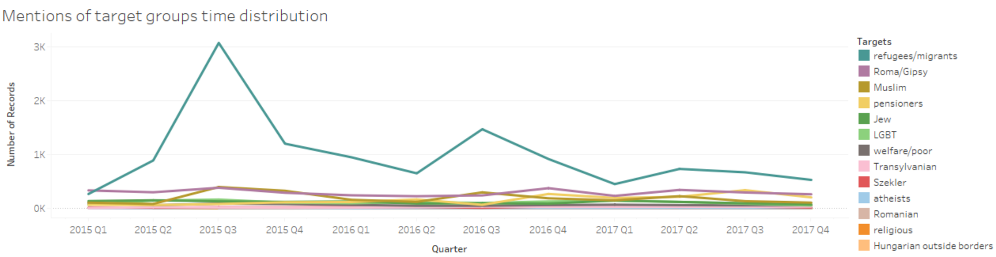

Figure 4. Mentions of target groups in the Hungarian sample by time frame quarter

Delving further into the context of mentions of target groups, co-occurrence analysis was used to trace the connections between targets of hate speech and other concepts. Communities were identified as modular, better connected components of the graph created by defining edges between concepts (targets, institutions, negative qualifiers, current themes as defined by codes based on semantic families) and using semi-automated coding in KH Coder. These communities may be interpreted as discursive patterns that define connections between targets of hate speech and the concepts represented thereby. Jaccard distance/similarity coefficients lower than 0.1 indicate low significance for the edges represented as dotted lines.

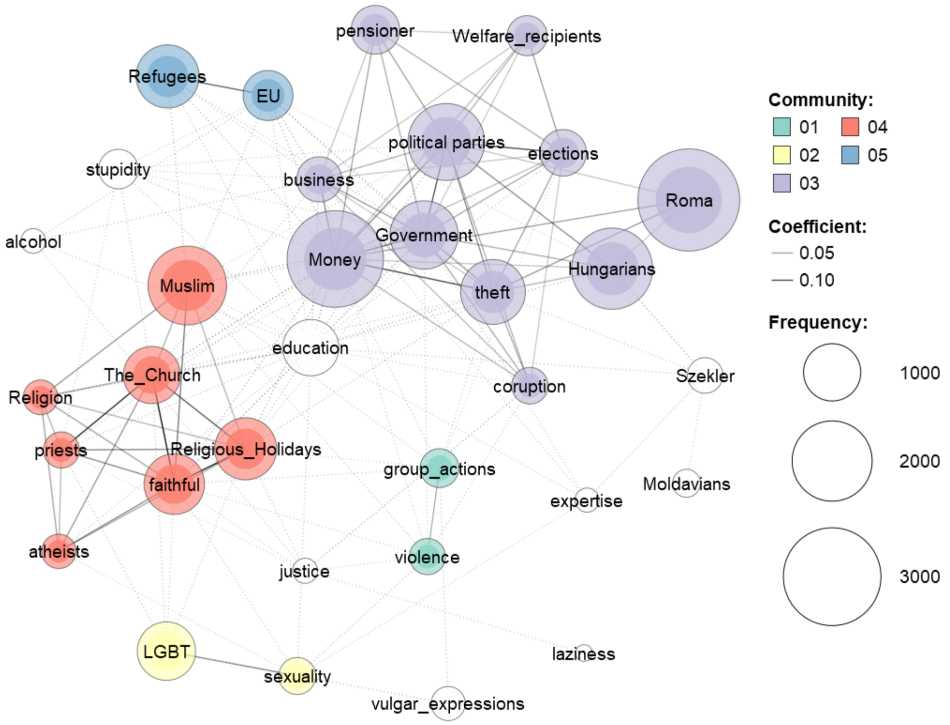

Figure 5. Co-occurrence network of terms referring to targets, negative qualifiers, institutions and current themes in the Romanian corpus

In the Romanian corpus, codes in the niche dictionaries that were used cover approximately 60 per cent of all comments. The three most frequently mentioned targets of hate speech are connected to political themes, in the context of elections, public spending, and corruption and theft. Hungarians are most likely to be mentioned in the context of the Democratic Union of Hungarians in Romania's participation in government or the ruling party coalition. It is worth investigating further whether mentions of *Roma* target the ethnic minority group or other groups by association. Unsurprisingly, mentions of *LGBT* minorities are linked to the concept of sexuality and sexually charged terms, whereas refugees seem to be mentioned mostly in the context of the EU. Religious themes and religious minority targets are connected, but have few and weak connections with other targets or concepts. Connections between mentions of *the Church* and *money* or *education*, *Muslims* and *refugees*, and the *faithful*, *priests* and *LGBT* are also worth investigating further.

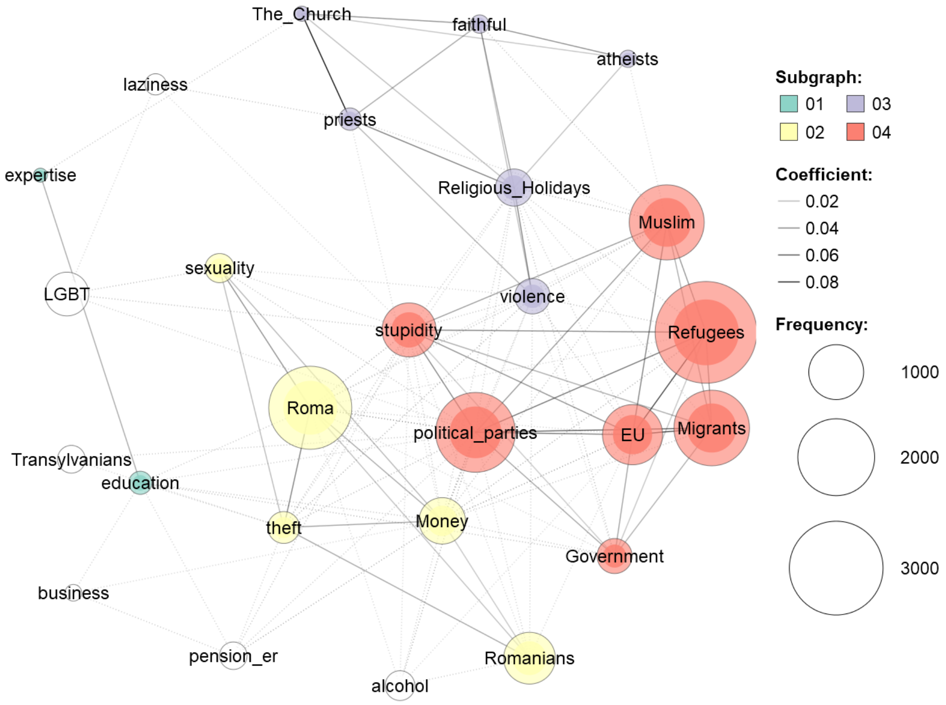

Figure 6. Co-occurrence network of terms referring to targets, negative qualifiers, institutions and current themes in the Hungarian corpus

In the case of the Hungarian corpus, codes in the niche dictionaries that were used cover approximately 48 per cent of all comments. The communities that were detected indicate prominent discursive patterns connecting the issue of refugees and migrants with the EU, government and political party. It is worth noting that negative qualifiers associated with stupidity often co-occur in these contexts, which may mean that offensive expressions were being used towards the target groups or were associated with the activity of the EU, the government or political parties in Hungary. Mentions of *alcohol* in this subgraph are perhaps worth investigating further to check for potential coding errors. The community of religious institutions and religion-related positioning is connected to *violence*, but references to *Muslims* appear more closely linked to conversations including mentions of refugees. It is worth noting that mentions of *violence* appear in contexts related to *refugees*, *Muslims*, *religious holidays*, *government* and *stupidity*. These may be connected to the coverage and aftermath of the Cologne 2015/2016 New Year's Eve attacks but require further investigation. The second most often mentioned of the target groups, the *Roma*, are connected with expressions of sexuality (possibly explicit insults) and the concept of theft, mirroring a negative stereotype about the target group. Mentions of Romanians also appear in the same cluster as the Roma group. Most frequently, the co-occurrence of the two targets – Romanians and Roma – indicate members of the Roma community who live or travel abroad and are associated with theft – commonly referred to during the last decades as Romanian Gypsies by both international media and Romanian citizens. Mentions of LGBT, although relatively frequent, do not co-occur frequently with other targets or concepts defined in the niche dictionaries for this analysis.

To summarize the findings, frequent targets of hate speech vary in importance in the two national contexts and their prominence is most likely influenced by the news media and political agenda – as pointed out by the analysis of the temporal contexts. However, the Roma group is the second most frequently mentioned in both corpora, and is discursively connected with the concept of theft, which may be interpreted as a prominent negative stereotype in both national/linguistic cultures. For the Hungarian pages, Transylvanians, Szeklers and Hungarians living abroad are categories that have some prominence, but little connection to the main discursive areas. However, for the Romanian pages, Hungarians are connected to the most prominent discursive area, probably due to the activity of the Democratic Union of Hungarians in Romania, but also likely due to some incidences of nationalist discourse directed at the Hungarian minority in Transylvania. The issue of refugees and migration is in both cases connected to the EU, but in the case of the Hungarian corpus it appears in central discursive patterns, whereas in the Romanian corpus it is marginal.

7. Conclusion

The analysis of targets of hate speech using computational or digital social science approaches and a large corpora of texts collected from social media platforms requires flexible, innovative research approaches, especially for languages such as Hungarian and Romanian, in the context of which natural language processing tools and resources adapted for the specific needs of social science researchers are still scarce. However, by using a niche dictionary text-mining approach coupled with co-occurrence network analysis this research has generated relevant insights into discourses involving groups which are frequently targeted by hate speech in the Romanian and Hungarian national contexts. Furthermore, placing this approach in the broader emerging theoretical framework of Network Agenda Setting allows for interpretations that relate discursive patterns in user comments with the media and political agendas as communicated by news outlets, politicians and political groups.

The comparative overview of the findings revealed by the analysis of the two corpora using the same methodology indicates connections between the media and political agendas and discursive patterns as manifested in Facebook comments. Furthermore, it indicates connections between specific targets and concepts that highlight broader issues or negative qualifiers that indicate common stereotypes. This exploratory research opens up questions for further research that may involve improved semi-automated coding, qualitative analysis of significant cases and methodological developments driven by the future development of machine learning for automated text classification and entity recognition based on linguistic resources for the two languages. Further improvement of sampling strategies and concept-definition through niche dictionaries should be considered in future work. However, similar such work by researchers may be hindered by Facebook's increasing restrictions on accessing content (such as comments) posted in public contexts through its API.

References

Angi, D. and Bădescu, G. (2014) *Discursul Instigator la Ură în România ((English: Hate speech in Romania), Fundația pentru Dezvoltarea Societății Civile (English: Foundation for the Development of Civil Society),* Research report. Available at: http://www.fdsc.ro/library/files/studiul_diu_integral.pdf . Accessed: 06-01-2018

Boromisza-Habashi, D. (2011) Dismantling the Antiracist 'Hate Speech' Agenda in Hungary: An Ethno-Rhetorical Analysis. *Text and Talk*, 31(1): 1-19. DOI: https://doi.org/10.1515/text.2011.001

Clauset, A., Newman, M. E. and Moore, C. (2004) Finding Community Structure in Very Large Networks. *Physical Review E*, 70(6): 66111. DOI: https://doi.org/10.1103/physreve.70.066111

Danowski, J. A. (1993) Network Analysis of Message Content. *Progress in Communication Sciences*, 12, 198-221.

Gagliardone, I., Pohjonen, M., Zerai, A., Aynekulu, G., Stremlau, N., Bekalu, M. A., Moges, M. A. and Taflan, P. (2016) *Mechachal: Online Debates and Elections in Ethiopia.* Final Report: From Hate Speech to Engagement in Social Media. University of Oxford, Oxford. http://dx.doi.org/10.2139/ssrn.2831369

Gagliardone, I., Gal, D., Alves, T. and Martinez, G. (2015) *Countering Online Hate Speech.* Paris: UNESCO Publishing.

Guo, L. (2014) Toward the Third Level of Agenda-Setting Theory: A Network Agenda Setting Model. In: Johnson, T. (ed.) *Agenda Setting in a 2.0 World: New Agendas in Communication.* New York, NY: Routledge. 12-133. DOI: https://doi.org/10.4324/9780203735879

Hann, E., & Róna, D. (2017). Antiszemita előítéletesség a mai magyar társadalomban. Research report. Budapest: Tett és Védelem Alapítvány, Medián. Available at: http://tev.hu/wp-content/uploads/2017/04/TEV_Antiszemitizmus-tanulmany_2016.pdf. Accessed: 06-01-2018.

Heinze, E. (2013) Hate Speech and the Normative Foundations of Regulation. *International Journal of Law in Context*, 9(4): 590-617.

Higuchi, K. (2001) *Kh Coder: A Free Software for Quantitative Content Analysis or Text Mining.* Available at: http://khc.sourceforge.net/en . Accessed: 06-01-2018.

Keyling, T. and Jünger, J. (2013) *Facepager: An Application for Generic Data Retrieval Through APIs.* Source code Available at: https://github.com/strohne/Facepager . Accessed: 06-01-2018.

McCombs, M. E., Shaw, D. L. and Weaver, D. H. (2014) New Directions in Agenda-Setting Theory and Research. *Mass Communication and Society,* 17(6): 781-802. DOI: https://doi.org/10.1080/15205436.2014.964871

Lani, R. (ed.) (2014) *Hate Speech in Online media in South East Europe.* Tirana: Albanian Media Institute. Available at: http://www.institutemedia.org/Documents/PDF/Hate%20speech%20in%20online%20media%20in%20SEE.pdf . Accessed: 10-06-2018.

Meza, R. (2016) Hate Speech in the Romanian Online Media. *Journal of Media Research*, 9(3): 55-77.

Pál, G. (2015) A vitathatóság keretei: A gyűlöletbeszéd fogalmának jelentésmezői és a kérdéskör metaforizációja a magyar politikai diskurzusban (English: Frames of Disputeability: Fields of Meaning of Hate Talk and Metaphorization of Issues in Hungarian Political Discourse). *Studies in Political Science No.2.* Budapest: MTA-TK-PTI.
Available at: https://politologia.tk.mta.hu/uploads/files/SPS_PG2.pdf Accessed: 06-01-2018.

Smuk, P. (2015) Combating Nationalist Hate Speech by Legal Means – European Standards and Selected Case Studies from Hungary. In: Cordell, K. and Jajecznik, K. (eds.) *The Transformation of Nationalism in Central and Eastern Europe.* Warsaw: University of Warsaw. 63-77.

Non academic sources:

Allen, R. (2017) Hard Questions: Who Should Decide What Is Hate Speech in an Online Global Community?. *Facebook Newsroom*, 27 June. https://newsroom.fb.com/news/2017/06/hard-questions-hate-speech/. Accessed: 10-06-2018.

Auchard, E. (ed.) and ten Wolde, H. (2016) Facebook Outsources Fight Against Racist Posts in Germany. *Reuters*, 15 January. http://www.reuters.com/article/facebook-germany-idUSKCN0UT1GM. Accessed: 06-01-2018.

Community Standards. Facebook. Available at: https://www.facebook.com/communitystandards/hate_speech Accessed: 13-10-2018.

Constine, J. (2018) Facebook Reveals 25 Pages of Takedown Rules for Hate Speech and More. *TechChrunch*, 24 April. Available at: https://techcrunch.com/2018/04/24/facebook-content-rules/ Accessed: 13-10-2018.

Donahue, P. (2015) Merkel Confronts Facebook's Zuckerberg Over Policing Hate Posts. *Bloomberg.com*, 26 September. Available at: https://www.bloomberg.com/news/articles/2015-09-26/merkel-confronts-facebook-s-zuckerberg-over-policing-hate-posts . Accessed: 06-01-2018.

‘Elie Wiesel’ National Institute for the Study of the Holocaust in Romania (2016) *Raport cu Privire la Discursul Instigator la Ură Împotriva Evreilor şi Romilor în Social Media (English: Report on Hate Speech against Jews and Roma in Social Media).* Report. Bucharest: Institutul Naţional pentru Studierea Holocaustului din România ‘Elie Wiesel’. Available at: http://www.inshr-ew.ro/ro/files/proiecte/DIU/DIU_social_media_1.pdf . Accessed: 10-10-2018.

Hungary: Responding to 'Hate Speech' Country Report. London: Article 19, 2018. Available at https://www.article19.org/wp-content/uploads/2018/03/Hungary-WEB.pdf. Accessed: 06-01-2018.

Răileanu, R., Tabă, O., Szelmenczi, A., Codreanu, I., Diaconescu, L. and Martin, R. (2016) *Raport Anual cu Privire la Discursul Instigator la Ură 2014 - 2015 (English: Annual Report on Hate Speech 2014-2015).* Bucharest: Activewatch. http://activewatch.ro/Assets/Upload/files/Raport%20anual%20cu%20privire%20la%20discursul%20instigator%20la%20ura%202014%20-%202015(1).pdf . Accessed: 06-01-2018.

Scott, M. and Eddy, M. (2016) Facebook Runs Up Against German Hate Speech Laws. *The New York Times*, 28 November. Available at: http://www.nytimes.com/2016/11/28/technology/facebook-germany-hate-speech-fake-news.html . Accessed: 06-01-2018.

Appendix

Table 3. Sample of Romanian Facebook Pages.

Sample of Romanian Facebook Pages		
Pages	*Sources groups*	*Number of comments containing mentions of targets*
StirileProTV	*News Media*	*3214*
Romania TV	*News Media*	*203*
Realitatea.NET	*News Media*	*338*
Observator	*News Media*	*156*
Libertatea.ro	*News Media*	*196*
HotNews.ro	*News Media*	*452*
Gandul	*News Media*	*408*
Digi24	*News Media*	*861*
Cancan.ro	*News Media*	*111*
B1.ro	*News Media*	*681*
Adevărul	*News Media*	*552*
Trezirea la Realitate	*Online Communities / Other*	*457*
Sfantul Nectarie	*Online Communities / Other*	*105*
Romania, tara ta	*Online Communities / Other*	*9*
Romania mea	*Online Communities / Other*	*275*
Piata Universitatii	*Online Communities / Other*	*4*
Părintele Arsenie Boca	*Online Communities / Other*	*580*
Opriți finanțarea cultelor religioase	*Online Communities / Other*	*640*
Made in Romania	*Online Communities / Other*	*95*
Junimea	*Online Communities / Other*	*177*
Historia	*Online Communities / Other*	*399*
Frumusetile Romaniei	*Online Communities / Other*	*141*
Dracusorul Vesel	*Online Communities / Other*	*61*
BRomania	*Online Communities / Other*	*136*
Anonymous Romania	*Online Communities*	*116*

Sample of Romanian Facebook Pages		
Pages	*Sources groups*	*Number of comments containing mentions of targets*
	/ Other	
Uniunea Salvaţi România – USR	*Political Parties*	*208*
Platforma România 100	*Political Parties*	*15*
Partidul Social Democrat	*Political Parties*	*185*
Partidul Naţional Liberal	*Political Parties*	*521*
Partidul Mişcarea Populară	*Political Parties*	*155*
ALDE – Partidul Alianta Liberalilor si Democratilor	*Political Parties*	*83*
Victor Ponta	*Politicians*	*1319*
Remus Cernea	*Politicians*	*1984*
Raluca Turcan	*Politicians*	*354*
Ninel PEIA	*Politicians*	*350*
Monica Luisa Macovei	*Politicians*	*425*
Mircea Geoana	*Politicians*	*299*
Liviu Dragnea	*Politicians*	*579*
Klaus Iohannis	*Politicians*	*1166*
Gabriela Firea	*Politicians*	*119*
Elena Udrea	*Politicians*	*262*
Daniel Ghita	*Politicians*	*586*
Dacian Cioloş	*Politicians*	*604*
Cristian Ghinea	*Politicians*	*304*
Cosette Chichirău	*Politicians*	*50*
Calin Popescu Tariceanu	*Politicians*	*462*
Bogdan Diaconu	*Politicians*	*3024*
Alina Gorghiu	*Politicians*	*680*
Adrian Nastase	*Politicians*	*310*
Times New Roman	*Satire*	*768*
kmkz.ro	*Satire*	*577*
Kelemen Hunor	*Kelemen Hunor & RMDSZ*	*475*
RMDSZ	*Kelemen Hunor & RMDSZ*	*519*

Table 4. Sample of Hungarian Facebook Pages.

Sample of Hungarian Facebook Pages		
Pages	*Sources groups*	*Number of comments containing mentions of targets*
24.hu	*News Media*	*483*
444	*News Media*	*1035*
777	*News Media*	*90*
Alfahír Hírportál	*News Media*	*1157*
Blikk	*News Media*	*466*
Borsonline – Bors Szórakoztató Napilap	*News Media*	*193*
HVG	*News Media*	*921*
Index.hu	*News Media*	*1186*
Magyar Hírlap	*News Media*	*528*
ORIGO	*News Media*	*202*
Rádió 1	*News Media*	*61*
TV2	*News Media*	*54*
5perc.es	*Online Communities*	*5*
A magyar lányok a legszebbek	*Online Communities*	*13*
Ablak – Zsiráf	*Online Communities*	*163*
Gondoltad volna?	*Online Communities*	*470*
I ♥ ALVÁS	*Online Communities*	*23*
Közös Ország Mozgalom	*Online Communities*	*35*
Kvíz Játékok	*Online Communities*	*9*
Love.hu	*Online Communities*	*10*
Mi folyik itt?	*Online Communities*	*7*
Szeretlek Magyarország	*Online Communities*	*40*
Tibi atya	*Online Communities*	*451*
Tiltakozás a sok értelmetlen tüntetés ellen	*Online Communities*	*222*
TrollFoci	*Online Communities*	*452*
Tudtad-e?	*Online Communities*	*403*
Ütős	*Online Communities*	*22*
Viszlát, kétharmad	*Online Communities*	*13*
Demokratikus Koalíció	*Political Parties*	*311*
Együtt	*Political Parties*	*1173*
Fidesz	*Political Parties*	*3532*
Jobbik Magyarországért Mozgalom	*Political Parties*	*1960*
KDNP és Frakciója	*Political Parties*	*98*
LMP – Lehet Más a Politika	*Political Parties*	*330*
Magyar Kétfarkú Kutya	*Political Parties*	*799*

Sample of Hungarian Facebook Pages		
Pages	*Sources groups*	*Number of comments containing mentions of targets*
Párt		
MSZP	*Political Parties*	*565*
Párbeszéd Magyarországért	*Political Parties*	*56*
Fodor Gábor	*Politicians*	*618*
Gyurcsány Ferenc	*Politicians*	*870*
Hadházy Ákos	*Politicians*	*527*
Juhász Péter	*Politicians*	*805*
Karácsony Gergely	*Politicians*	*511*
Molnár Gyula	*Politicians*	*104*
Niedermüller Péter	*Politicians*	*427*
Orbán Viktor	*Politicians*	*454*
Semjén Zsolt	*Politicians*	*3*
Szabó Tímea	*Politicians*	*473*
Szél Bernadett	*Politicians*	*521*
Toroczkai László	*Politicians*	*2526*
Volner János	*Politicians*	*349*
Vona Gábor	*Politicians*	*2232*

Comments containing references to target groups (RO)

Facebook Page Categories	Page	Targets (RO) Null	welfare/poor	Roma/Gipsy	Hungarian	Muslim	refugees/migrants	LGBT	pensioners	religious	Jew	Transylvanian	atheists	Szekler
News Media	Adevărul	96,61%	0,69%	0,42%	0,51%	0,61%	0,32%	0,33%	0,18%	0,05%	0,15%	0,04%	0,04%	0,07%
	B1.ro	97,52%	0,43%	0,46%	0,44%	0,45%	0,19%	0,12%	0,20%	0,06%	0,05%	0,04%	0,02%	0,02%
	Cancan.ro	98,86%	0,29%	0,67%		0,02%	0,02%	0,07%	0,03%	0,03%	0,01%			
	Digi24	96,59%	0,64%	0,34%	0,47%	0,61%	0,66%	0,13%	0,29%	0,06%	0,14%	0,06%	0,00%	0,02%
	Gandul	96,88%	0,60%	0,63%	0,50%	0,36%	0,37%	0,18%	0,20%	0,06%	0,11%	0,02%		0,09%
	HotNews.ro	97,63%	0,69%	0,23%	0,30%	0,23%	0,20%	0,22%	0,28%	0,08%	0,07%	0,04%		0,03%
	Libertatea.ro	98,51%	0,30%	0,61%	0,08%	0,05%	0,02%	0,11%	0,23%	0,04%	0,07%			
	Observator	98,59%	0,38%	0,34%	0,05%	0,25%	0,09%	0,15%	0,04%	0,08%	0,01%			0,02%
	Realitatea.NET	97,76%	0,53%	0,46%	0,26%	0,42%	0,11%	0,11%	0,16%	0,06%	0,07%	0,05%	0,01%	
	Romania TV	97,46%	0,49%	1,44%	0,08%	0,06%	0,01%	0,19%	0,15%	0,08%	0,01%	0,03%		0,01%
	StirileProTV	98,44%	0,48%	0,51%	0,09%	0,15%	0,08%	0,08%	0,09%	0,04%	0,02%	0,02%	0,00%	0,01%
Online Communities	Anonymous Romania	97,48%	0,33%	0,35%	0,28%	0,28%	0,15%	0,24%	0,09%	0,07%	0,65%		0,09%	
	BRomania	99,43%	0,05%	0,06%	0,07%	0,01%	0,02%	0,19%	0,01%	0,03%	0,02%	0,09%		0,01%
	Dracusorul Vesel	99,75%	0,08%	0,06%	0,03%	0,00%	0,02%	0,03%	0,02%	0,01%		0,01%		
	Frumusetile Romaniei	99,35%	0,28%	0,06%	0,04%	0,01%	0,01%		0,08%	0,08%		0,08%		0,00%
	Historia	95,60%	0,47%	0,64%	1,23%	0,33%	0,09%	0,09%	0,04%	0,09%	1,23%	0,09%	0,01%	0,08%
	Junimea	99,53%	0,01%	0,10%	0,17%	0,00%	0,01%	0,03%	0,00%	0,01%	0,02%	0,12%	0,01%	0,00%
	Made in Romania	99,23%	0,32%	0,10%	0,06%	0,07%	0,09%	0,01%	0,05%	0,03%	0,02%	0,02%		
	Opriți finanţarea cultelor ..	95,36%	1,17%	0,26%	0,09%	0,62%	0,06%	0,46%	0,09%	1,27%	0,12%	0,01%	0,47%	0,01%
	Părintele Arsenie Boca	95,66%	0,76%	0,18%	0,17%	1,03%	0,19%	0,35%	0,07%	1,06%	0,23%	0,04%	0,25%	
	Piata Universitatii	96,99%	2,26%		0,75%									
	Romania mea	98,73%	0,30%	0,36%	0,10%	0,23%	0,03%	0,02%	0,04%	0,10%	0,05%	0,02%	0,01%	0,01%
	Romania, tara ta	98,06%		1,08%	0,22%		0,43%			0,22%				
	Sfantul Nectarie	99,69%	0,09%	0,02%		0,00%	0,01%	0,01%	0,01%	0,15%	0,01%		0,01%	
	Trezirea la Realitate	93,76%	0,52%	0,56%	1,62%	0,87%	1,15%	0,48%	0,07%	0,11%	0,67%	0,03%	0,04%	0,12%
Political Parties	ALDE - Partidul Alianta Lib..	99,02%	0,26%	0,11%	0,22%		0,04%	0,01%	0,22%	0,02%		0,05%	0,01%	0,04%
	Partidul Mișcarea Populară	98,47%	0,34%	0,19%	0,27%	0,26%	0,23%	0,03%	0,17%		0,01%	0,03%	0,01%	0,01%
	Partidul Naţional Liberal	97,91%	0,73%	0,18%	0,23%	0,16%	0,23%	0,04%	0,36%	0,03%	0,06%	0,06%	0,01%	
	Partidul Social Democrat	97,65%	0,56%	0,04%	0,51%	0,17%	0,06%		0,83%	0,03%	0,08%	0,01%		0,08%
	Platforma România 100	98,54%	0,39%		0,10%	0,10%	0,19%	0,19%	0,29%			0,10%	0,10%	
	Uniunea Salvați România -..	98,06%	0,44%	0,12%	0,45%	0,07%	0,12%	0,35%	0,25%	0,02%	0,03%	0,06%	0,01%	0,02%
Politicians	Adrian Nastase	98,14%	0,58%	0,17%	0,36%	0,17%	0,20%	0,03%	0,14%	0,05%	0,05%	0,04%	0,02%	0,04%
	Alina Gorghiu	97,88%	0,86%	0,17%	0,21%	0,09%	0,12%	0,05%	0,47%	0,04%	0,04%	0,05%	0,01%	0,02%
	Bogdan Diaconu	88,07%	0,72%	2,22%	4,09%	1,75%	1,59%	0,64%	0,17%	0,05%	0,41%	0,05%	0,01%	0,22%
	Calin Popescu Tariceanu	97,57%	0,77%	0,18%	0,36%	0,12%	0,18%	0,07%	0,52%	0,04%	0,12%	0,03%	0,01%	0,02%
	Cosette Chichirău	98,88%	0,61%	0,07%	0,11%		0,02%	0,04%	0,13%		0,07%		0,02%	0,04%
	Cristian Ghinea	97,83%	0,56%	0,18%	0,42%	0,14%	0,25%	0,25%	0,17%	0,06%	0,01%	0,02%	0,08%	0,03%
	Dacian Cioloș	93,67%	2,35%	0,38%	0,39%	0,48%	0,99%	0,08%	0,87%	0,14%	0,12%	0,49%	0,03%	0,02%
	Daniel Ghita	96,06%	0,64%	0,36%	1,08%	0,48%	0,56%	0,24%	0,09%	0,07%	0,17%	0,07%	0,04%	0,13%
	Elena Udrea	98,01%	0,76%	0,09%	0,06%	0,24%	0,25%	0,02%	0,22%	0,27%	0,04%	0,01%	0,03%	
	Gabriela Firea	99,52%	0,08%	0,02%	0,03%	0,03%	0,02%	0,01%	0,17%	0,08%	0,04%	0,01%	0,00%	
	Klaus Iohannis	92,66%	1,98%	0,55%	0,64%	1,19%	1,61%	0,13%	0,47%	0,11%	0,39%	0,17%	0,04%	0,08%
	Liviu Dragnea	95,41%	1,55%	0,25%	0,45%	0,48%	0,31%	0,06%	1,22%	0,03%	0,18%	0,05%		0,01%
	Mircea Geoana	97,21%	0,74%	0,29%	0,20%	0,56%	0,63%	0,07%	0,14%	0,05%	0,08%	0,04%	0,01%	
	Monica Luisa Macovei	97,65%	0,47%	0,18%	0,28%	0,48%	0,55%	0,08%	0,10%	0,07%	0,04%	0,03%	0,02%	0,06%
	Ninel PEIA	96,27%	0,87%	0,31%	0,71%	0,22%	0,51%	0,22%	0,27%	0,22%	0,22%	0,04%	0,11%	0,01%
	Raluca Turcan	98,10%	0,87%	0,09%	0,14%	0,09%	0,06%	0,08%	0,41%	0,02%	0,01%	0,10%	0,01%	0,02%
	Remus Cernea	90,87%	0,56%	0,40%	0,17%	1,20%	0,46%	4,48%	0,06%	0,74%	0,27%	0,02%	0,78%	0,01%
	Victor Ponta	96,25%	1,10%	0,17%	0,44%	0,51%	0,37%	0,05%	0,88%	0,08%	0,07%	0,05%	0,00%	0,03%
Satire	kmkz.ro	98,01%	0,42%	0,46%	0,21%	0,15%	0,06%	0,19%	0,30%	0,06%	0,04%	0,06%	0,01%	0,03%
	Times New Roman	97,07%	0,29%	0,53%	0,74%	0,19%	0,13%	0,24%	0,31%	0,08%	0,06%	0,22%	0,05%	0,09%

Figure 7. Percentages of comments containing mentions of targets on Romanian pages.

Comments containing references to target groups (HU)

		Targets (HU)													
Facebook Page Categories	Page	Null	refugees/migra..	Roma/Gipsy	Muslim	pensioners	Jew	LGBT	welfare/poor	Szekler	Transylvanian	atheists	Romanian	religious	Hungarian outside borders
News Media	24.hu	97,96%	0,93%	0,22%	0,27%	0,12%	0,16%	0,21%	0,08%	0,03%	0,01%	0,00%			
	444	96,52%	1,72%	0,38%	0,46%	0,14%	0,28%	0,30%	0,06%	0,07%	0,03%	0,02%			
	777	97,18%	0,53%		0,86%	0,03%	0,30%	0,76%		0,10%	0,03%	0,20%			
	Alfahír Hírportál	94,87%	2,17%	1,14%	0,71%	0,29%	0,24%	0,14%	0,22%	0,12%	0,05%	0,02%	0,02%	0,01%	
	Blikk	98,25%	0,73%	0,34%	0,11%	0,08%	0,12%	0,29%	0,04%	0,00%	0,02%	0,01%			
	Borsonline - Bors Szórako..	98,96%	0,40%	0,22%	0,08%	0,08%	0,06%	0,15%	0,02%	0,02%	0,01%		0,01%		
	HVG	96,27%	2,19%	0,38%	0,33%	0,24%	0,16%	0,19%	0,11%	0,05%	0,07%	0,00%			0,00%
	Index.hu	96,35%	1,97%	0,35%	0,62%	0,16%	0,20%	0,14%	0,13%	0,04%	0,02%	0,02%			
	Magyar Hírlap	93,98%	3,50%	0,37%	0,87%	0,15%	0,61%	0,29%	0,08%	0,12%	0,02%		0,01%		
	ORIGO	98,82%	0,60%	0,13%	0,08%	0,05%	0,08%	0,14%	0,04%	0,03%	0,01%	0,03%			
	Rádió 1	99,84%	0,03%	0,01%	0,00%	0,00%		0,02%		0,05%	0,02%	0,00%			
	TV2	99,77%	0,08%	0,07%		0,03%	0,01%	0,05%							
Online Communities	5perc.es	99,92%		0,04%						0,04%					
	A magyar lányok a legsze..	99,86%	0,01%	0,03%	0,02%	0,01%		0,02%		0,02%	0,01%				
	Ablak - Zsiráf	98,76%	0,27%	0,26%	0,21%	0,10%	0,04%	0,18%	0,13%	0,02%	0,01%	0,02%			
	Gondoltad volna?	99,05%	0,26%	0,15%	0,04%	0,03%	0,12%	0,24%	0,01%	0,07%	0,01%	0,01%			
	I ♥ ALVÁS	99,29%	0,23%	0,19%	0,08%			0,15%	0,04%	0,04%					
	Közös Ország Mozgalom	99,03%	0,45%	0,08%	0,08%	0,08%		0,08%	0,04%	0,04%	0,08%	0,04%			
	Kvíz Játékok	99,87%	0,02%	0,05%		0,04%				0,02%					
	Love.hu	99,88%	0,02%				0,02%	0,02%		0,06%					
	Mi folyik itt?	99,84%						0,11%		0,05%					
	Szeretlek Magyarország	99,57%	0,10%	0,04%	0,10%		0,08%	0,06%	0,03%	0,01%	0,01%				
	Tibi atya	99,20%	0,11%	0,18%	0,04%	0,05%	0,04%	0,25%	0,01%	0,07%	0,03%	0,01%	0,00%		
	Tiltakozás a sok értelmetl..	96,53%	1,79%	0,15%	0,39%	0,20%	0,37%	0,28%	0,18%	0,07%	0,05%				
	TrollFoci	99,51%	0,04%	0,03%		0,02%	0,00%	0,29%	0,00%	0,07%	0,02%		0,01%		
	Tudtad-e?	99,23%	0,19%	0,10%	0,04%	0,05%	0,09%	0,19%	0,03%	0,05%	0,02%	0,00%		0,00%	
	Ütős	99,76%	0,04%	0,02%		0,02%		0,11%		0,06%					
	Viszlát, kétharmad	98,66%	0,45%	0,22%	0,45%				0,22%						
Political Parties	Demokratikus Koalíció	98,43%	0,59%	0,07%	0,06%	0,66%	0,02%	0,01%	0,06%	0,04%	0,06%		0,01%		0,01%
	Együtt	96,15%	1,95%	0,51%	0,37%	0,26%	0,30%	0,17%	0,16%	0,03%	0,07%	0,01%	0,01%		0,00%
	Fidesz	89,94%	7,21%	0,37%	1,24%	0,39%	0,25%	0,14%	0,29%	0,07%	0,06%	0,04%	0,00%		
	Jobbik Magyarországért ..	94,48%	2,12%	1,20%	0,35%	0,61%	0,57%	0,22%	0,24%	0,10%	0,08%	0,01%	0,02%		
	KDNP és Frakciója	96,65%	1,83%	0,15%	0,53%	0,27%	0,34%		0,04%	0,04%	0,11%	0,04%			
	LMP - Lehet Más a Politika	96,92%	1,38%	0,48%	0,23%	0,40%	0,13%	0,16%	0,22%	0,03%	0,04%	0,01%			
	Magyar Kétfarkú Kutya P..	97,41%	1,76%	0,10%	0,16%	0,18%	0,18%	0,10%	0,04%	0,04%	0,02%	0,00%			
	MSZP	98,09%	0,79%	0,18%	0,10%	0,60%	0,02%	0,01%	0,14%	0,01%	0,04%		0,01%	0,00%	
	Párbeszéd Magyarország..	98,24%	0,60%	0,25%	0,07%	0,42%	0,07%	0,14%	0,14%		0,07%				
Politicians	Fodor Gábor	95,69%	2,53%	0,46%	0,67%	0,07%	0,16%	0,28%	0,09%	0,02%		0,01%	0,01%		
	Gyurcsány Ferenc	96,15%	2,10%	0,28%	0,24%	0,72%	0,10%	0,01%	0,13%	0,07%	0,18%	0,01%	0,01%		
	Hadházy Ákos	97,05%	0,62%	1,71%	0,04%	0,29%	0,05%	0,04%	0,09%	0,02%	0,06%	0,01%	0,01%	0,01%	
	Juhász Péter	97,47%	1,29%	0,29%	0,19%	0,27%	0,10%	0,26%	0,05%	0,03%	0,04%	0,01%	0,00%	0,01%	
	Karácsony Gergely	98,05%	0,67%	0,29%	0,11%	0,29%	0,17%	0,07%	0,21%	0,09%	0,04%		0,00%		
	Molnár Gyula	97,93%	1,01%	0,07%	0,17%	0,63%		0,05%	0,02%		0,10%	0,02%			
	Niedermüller Péter	91,95%	5,04%	0,90%	0,82%	0,33%	0,45%	0,14%	0,16%	0,02%	0,16%	0,02%	0,02%		
	Orbán Viktor	97,47%	1,34%	0,12%	0,33%	0,24%	0,10%	0,11%	0,05%	0,15%	0,07%	0,02%			
	Semjén Zsolt	98,60%	1,40%												
	Szabó Tímea	96,67%	1,56%	0,46%	0,16%	0,54%	0,13%	0,17%	0,25%	0,02%	0,03%	0,02%		0,01%	
	Szél Bernadett	97,79%	0,91%	0,30%	0,17%	0,21%	0,11%	0,16%	0,20%	0,06%	0,08%	0,00%			
	Toroczkai László	89,66%	6,02%	0,78%	1,97%	0,08%	0,75%	0,27%	0,28%	0,09%	0,05%	0,05%	0,00%	0,01%	
	Volner János	94,25%	1,87%	1,45%	0,28%	0,97%	0,55%	0,28%	0,21%	0,11%			0,04%		
	Vona Gábor	94,35%	2,24%	1,07%	0,48%	0,74%	0,48%	0,22%	0,16%	0,11%	0,11%	0,03%	0,01%	0,01%	

Figure 8. Percentage of comments containing mentions of targets on Hungarian pages.