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Sommario

Hate speech predicts engagement on social media: A case study from Turkey

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Abstract

What drives engagement on social media has been the focus of social scientific inquiry especially in recent years. Among various established predictors of virality on social media are emotional language, language about in- and out-groups, and notions of positivity and negativity. In light of prior work, this study explores whether hate speech in the form of demonization of a social group is associated with engagement on social media by using a case study from Turkey: The Gülen Movement (GM), a once-admired social movement that has been going through a decade-long demonization, stigmatization, criminalization and persecution. The results show that demonizing language against GM (a specific out-group) is a strong predictor of virality in three of the largest social media platforms in Turkey's social media ecosystem: Facebook, Instagram and Twitter. The results also show that demonizing language about a specific out-group has the largest effect size compared to other well-established predictors of virality such as the moral-emotional language, language about the in-group and language about the (general) out-group.

Keywords

Hate speech, demonization, social-media, specific out-group, Gülen Movement, Turkey

1. Introduction

Social media has become a crucial aspect of our lives over the last two decades, as evidenced by the existence of 4.6 billion people active social media users in the world (Dixon, 2022). Accordingly, scholars and researchers have looked at various issues related to social media, such as how users interact, how people's preferences and behaviour are shaped by social media and how information diffuses on these platforms and apps. Pariser (2011), for example, described how social media put people into "filter bubbles" through ranking algorithms, which are engaged in passive personalization without any active participation by users. Other studies highlighted the "echo chamber effect" of social media by proposing that users online have a proclivity to favour information conforming their worldviews and ignore opposing information (Cinelli et al., 2021), and that "selective exposure is the primary driver of content diffusion and generates the formation of homogenous clusters." (Del Vicario et al., 2016). An Echo chamber is defined as "opinion, political leaning, or belief of users about a topic gets reinforced due to repeated interactions with peers or sources having similar tendencies and attitudes" (Cinelli et al., 2021, p. 1). These concepts have especially influenced research that focus on polarization and virality on social media. In-group bias—the tendency to evaluate the ingroup more favourably than the out-group—for example, has been one of the key elements of psychological research (Brewer, 1979), and evidence for social media limited to Twitter already suggests that users retweet in-group members at much higher rates than out-group members (Shin et al., 2017). In contrast, a recent study examining engagement on social media has shown that in polarized contexts outgroup animosity is the strongest predictor of virality on Facebook and Twitter (Rathje et al. (2021).

In understanding the diffusion of online content, some studies took psychological approaches and focused on 'emotions.' One study found that "expression of moral emotion is key for the spread of moral and political ideas in online social networks," a process it called "moral contagion" (Brady et al., 2017). Others focused on the notions of positivity and negativity, as one study argued that "high-arousal positive (awe) or negative (anger or anxiety) emotions is more viral… content that evokes low-arousal, or deactivating, emotions (e.g., sadness) is less viral (Berger & Milkman, 2012). Similarly, an expert report examining 'negativity' in legislator's outreach to public in the

United States found that partisan criticism produces the most engagement on social media (Messing & Weisel, 2017).

Hate speech on or through social media has also become a focus of scientific inquiry, especially in recent years. A comprehensive report focusing on global comparisons posited that algorithms mediate users' experience to maximize their engagement, which often unintentionally lead to the promotion of extreme content as well as increased violence attributed to online hate speech (Laub, 2019). Comparing six social media platforms, another recent research demonstrated these effects in two separate contexts. First that "malicious COVID-19 content, including racism, disinformation, and misinformation, exploits the multiverse of online hate to spread quickly beyond the control of any individual social media platform" (Velásquez et al., 2021). More recently, a study on the far-right networking site 'Gab.com' has found that "hateful content diffuse farther, wider and faster and have a greater outreach than those of non-hateful users" (Mathew et al., 2018).

The shared concern in all these studies is the notion of polarization and diminished mutual understanding, which ultimately place people "so far apart that they have no common ground—effectively inhabiting different realities" (Arguedas et al., 2022). In light of these studies, this study will explore whether hate speech in the form of demonization of a social group is associated with engagement on social media through a case study from Turkey: The Gülen Movement (GM), a once-admired social movement that has been going through a decade-long demonization, stigmatization, criminalization and persecution.[1] In accord with Facebook and Twitter, this paper define hate speech as a direct attack on people based on certain characteristics—race, ethnicity, national origin, religious affiliation, sexual orientation, caste, sex, gender identity, and serious disease or disability; a direct attack as violent or dehumanizing speech, statements of inferiority, or calls for exclusion or segregation (Facebook, 2023), or as promotion of violence against or direct attacks or threats on other people on the basis of the said characteristics (Twitter, 2023). In what follows, I will first provide a brief background on the socio-political context, within which the GM is embedded, and continue with sections on data, methods and analyses.

[1] For a detailed account about the persecution of individuals who are associated with the Gulen Movement, see, for example, Paul Weller, 2022. *Fethullah Gülen's Teaching and Practice: Inheritance, Context, and Interactive Development.* Palgrave Macmillan: Switzerland, p.ix, p.97. (https://doi.org/10.1007/978-3-030-97363-6).

2. Socio-Political Context

Originating from Turkey, the GM, also known as the *Hizmet (Service) Movement*, is led by Fethullah Gülen, a charismatic scholar and cleric who since 1999 is in self-imposed exile in Pennsylvania, USA. The movement is defined as an Islam-inspired grassroots civil society movement that operates in over 160 countries (Keles & Sezgin, 2015). The movement's goals, structure, and modus operandi, however, render it as a controversial, non-traditional civil society movement. As Fitzgerald (2017) puts it,

> The GMs' focus on individual transformation and religious practices suggests that it is a religious movement; its extensive outreach into various institutions (i.e., education, health care, and media) suggests a social movement seeking legitimacy and broad social change; its purported infiltration of key government and military offices suggests a political movement.

Domestically, a distinct aspect of the GM over four decades has been its ability to establish good relationships with almost every incumbent government, regardless of their ideological underpinnings (e.g., Islamist, centrist, secular, or leftist). In doing so, the movement implemented a strategy of negotiation and avoided confrontation (Turam, 2006), which some scholars described as "strategic non-confrontation" (Gurbuz & Bernstein, 2012). This strategy manifested itself best at the movement's relations with Recep Tayyip Erdoğan's Justice and Development Party (The AKP), which has been in power since 2002.[2] The positive relationship between the two for about a decade has long been dubbed "an alliance," largely due to their perceived ideological affinity and references to Islam. Unlike assumed by many, however, the so-called alliance between the AKP and the GM was not based on their ideology or pro-Islamic worldviews. It was indeed the product of a strategic approach by each party, in that Erdoğan enjoyed the political support of the GM, whereas the GM was happy with the opportunity space 'allowed for them' in both civil and political society.

This symbiotic relationship started to dwindle due to a series of events starting around 2011, These include i) a reshuffling of personnel in the security bureaucracy starting; ii) the summoning of Hakan Fidan, the head of the Turkish Central Intelligence Organization (MIT) in February 2012, by a public prosecutor as a suspect over his talks[3] with several leaders of the outlawed PKK terrorist organi-

[2] Due to Erdoğan's initial pro-Western, all-inclusive and seemingly accountable policies, Turkey was once shown as a role-model for undemocratic states in the Middle East, Central Asia and the Balkans. From 2010 onwards, however, his leadership style became increasingly oppressive and authoritarian, which led to Turkey's backsliding from democracy and respect for human rights, the rule of law and the constitution.

[3] Erdogan later stated that it was him who sent Hakan Fidan to have the mentioned talks with those PKK leaders. See, Institutkurde.org (2013). "Turkey's 'secret-keeper': spy chief Hakan

zation in Oslo; iii) the government's decision to close all university preparation schools (*dershanes* in Turkish) in November 2013; and iv) the corruption allegations against four cabinet ministers on 17-25 December 2013, which also implicated Erdoğan (then the Prime Minister) and several of his family members. The first and third of these events have largely been understood as a move by Erdoğan/AKP against the GM, whereas the second and fourth as the latter's response to those moves. The last event (the corruption scandal) was the turning point at which Erdoğan declared the GM as an enemy.

As it was argued in a prior study by Yilmaz & Sozer (2015), Erdoğan emerged victorious from this tug-of-war with the GM by embarking *inter alia* on a political project by which GM was not only portrayed as Erdoğan's personal enemy, but it was also socially reconstructed as a parallel state[4] and a terrorist organization threatening the very existence of the state. This was achieved/attempted through political *discourse* which is mainly focused on rhetoric- the art of persuasion and manipulation (Chilton & Schäffner, 2011) to achieve dominance over others in politics (Fairclough, 2000). This often involves identity construction of a group as an enemy and pitting it against one's in-group, as research has shown that the level of collective self-esteem predicts out-group derogation, "when a valued social identity is on trial," i.e., 'threatened' (Branscombe and Wann, 1994). In line with these concepts, especially after 2013, words and phrases like 'parallel state,' 'gang of chaos,' 'mobster Lobby,' 'slugs,' 'bloodsucking vampires,' or 'insidious terrorist organization' were used as the GM became the main motifs of Erdoğan's speeches in both domestic and international realms. This was aimed at consolidating his power base around the idea that Turkish state values and identities — e.g., national, AKP or religious — are under threat coming from a constructed enemy, which he called Fethullahist Terrorist Organization (FETÖ, in Turkish).

The watershed moment for the GM was the coup attempt July 15, 2016. On that day, a military coup attempt took place in Turkey, during which, according to the Turkish government, 246 people were killed amid resistance to the coup, 179 of them civilians, and 2,000 were wounded (Ward, 2016). Within the first minutes of the coup, Erdoğan and like-minded individuals and groups alleged that Gülenist officers in the army were behind the coup. In the subsequent days and

Fidan." Available at: https://www.institutkurde.org/en/info/latest/turkey-s-secret-keeper-spy-chief-hakan-fidan-3710.

[4] The term parallel state is described as "…an institutional arrangement within which organised interests with criminal capacities or expertise in the use of violence use their links with the formal state to protect and expand their activities. It perpetuates state weakness while maintaining the appearance of legitimacy." For more info, see, Briscoe I., 2008, 'The Proliferation of the 'Parallel State", Fundación para las Relaciones Internacionales y el Diálogo Exterior (FRIDE), Madrid. Available at: https://gsdrc.org/document-library/the-proliferation-of-the-parallel-state.

months, Erdoğan declared a state of emergency and launched a campaign of an unprecedented purge and incarceration to, in his own words, "clean all the virus of Gülen supporters from the army" (Guardian, 2016). This campaign was not limited to army officers, nonetheless, as it turned into a witch-hunt targeting civil servants from other ministries (e.g., judges, prosecutors, police officers, academics, teachers), businesspeople, journalists and ordinary citizens, as well as their family members.[5] The current numbers related to post-coup crackdown as of April 2022, as compiled by a small group of young journalists, are as follows: 150,348 civil servants were dismissed (which include 6,021 academics, and 4,463 judges and prosecutors); 597,793 people were investigated; 94,975 individuals were arrested; 3,003 schools, dormitories and universities were closed; 189 media outlets were shut down (Turkeypurge, 2023).[6]

To sum up, since his fall out with the Gülen Movement in 2013, Erdoğan has consistently used the othering words "FETÖ," its derivatives and other 'demonizing' words to maintain legitimacy to his questioned authority and consolidate his constituency, whose belief and trust in Erdoğan has been eroding conspicuously. More importantly, Erdoğan constructed and framed the discourse against this movement in such a way that it became a standard in gauging citizens' loyalty to the Turkish state. Due to the coercive effects of this standard, Turkish people today are compelled to reveal their opinion about the GM, and this has enormous legal, socio-political, and economic ramifications for them. To specify, being simply viewed as pro-GM may result in a person being indicted or imprisoned, getting fired from his/her job and to be subjected to exclusion or even 'civil death' in social life. Even being neutral to this group, or hesitating to utter the word "FETÖ" openly, may result in similar outcomes for ordinary Turkish citizens.

Proceeding from the abovementioned concepts and background, it is expected that demonization of the GM would have a significant impact on virality on Turkey's social media ecosystem. To test this hypothesis, I first conducted a community detection analysis to explore who are amplifying the word "FETÖ" on Facebook by mapping out users' file-sharing behaviours. Based on the results of this analysis, I spotted the largest bubbles and selected three types of media from them to focus on, namely: *Pro-AKP media*, *Liberal-Kemalist media* and *Ulusalcı (Ultra-nationalist*) media. Next, using the official accounts of these media outlets, I downloaded data from three of the largest social media platforms: Facebook, Instagram and Twitter. Finally, I conducted statistical analyses to understand the role language demonizing the GM played in predicting shares and retweets compared

[5] For the effects of the Turkish government's response to the coup attempt, see an article by (Ward, 2016), the Deputy Director of the Human Rights Watch.

[6] It should be noted that although the brunt of the crackdown was borne by the GM, other groups who opposed Erdogan regime were also affected by the post-coup crackdown (e.g., Kurds and Alevis).

to other established predictors of engagement or virality on social media such as political in-group language (Shin & Thorston, 2017), political out-group language (Rathje et al., 2021) and moral-emotional language (Brady et al, 2017; Messing & Weisel, 2017).

3. Material and Methods

To explore who, or which groups, amplify messages related to GM on social media, I downloaded a sample of Facebook data in March 2022 with the query "FETÖ" on CrowdTangle, a tool owned by Facebook that aggregates data from public pages, covering the dates from 1 June 2016 to 28 February 2022. The dataset contained 51,672[7] original FB Page posts, which received 2.5 million comments and 35 million total interactions (e.g., likes, shares, comments, reactions). The volume of these Facebook posts can be viewed in Supporting Information (SI) Appendix, Fig. S1. In determining community networks of demonizing speech against the GM, I mapped out users' link-sharing behaviours with the Gephi software,[8] where each "Page Name" was taken as a node and each URL link they shared as an edge between them (For the network graph, see SI Appendix, Fig. S2).

In the network graph, the biggest bubbles were news media outlets that are known for their pro-AKP stances, such as: Yeni Akit, Yeni Şafak, A Haber and Sabah, except for Sözcü and Cumhuriyet, which are largely considered as opposition, or anti-Erdoğan/anti-AKP. Some of the larger bubbles, e.g., ODA TV and Aydınlık, had a mixed stance in politics given that they support Erdoğan and the AKP in certain issues (e.g., his rapprochement with Russia and clamping down on the GM) while being at odds with them in others (e.g., Erdoğan's conservative or "Islamist" worldview). In an effort to facilitate our next step, I selected several media from the foregoing network graph and categorized them into three groups: 1) *Pro-AKP Media* (Yeni Akit, Sabah, AHaber); 2) *Liberal-Kemalist Media* (Sözcü, Cumhuriyet); and 3) *Ulusalcı Media* (ODA TV, Aydınlık). It should be noted that all three groups are against the GM today, but it was not always the case. Before the corruption allegations in 2013, many people with Pro-AKP and Liberal-Kemalist views had sympathy towards the movement for various reasons (its emphasis on education and promotion of Turkish culture abroad, for instance), but the third group has always been hostile to the GM.

[7] For community network analysis, I used a subset of data by removing empty rows under "Links" column, which yielded 50,949 posts.

[8] This network mapping was based on Christina Fan (2021), "Network Mapping with Gephi and CrowdTangle." Accessed online at: https://help.crowdtangle.com/en/articles/4495952-network-mapping-with-gephi-and-crowdtangle.

Having determined these groups, I then downloaded historical data on Twitter, Facebook, and Instagram by using their official accounts. The tweets were downloaded using the R package "academictwitteR" containing original tweets and retweets from 1 January 2012 to 03 February 2022, whereas Facebook and Instagram data were retrieved through Crowdtangle covering the dates from 1 June 2016 and 03 March 2022. Consequently, I analyzed 1) *Pro-AKP* Facebook posts (*n* = 516,863), Instagram posts (*n* = 28,780) and original tweets (*n* = 66,960); 2) *Liberal-Kemalist* Facebook posts (*n* =347,466), Instagram posts (*n* =25,791) and original tweets (*n* =29,838); and 3) *Ulusalcı* Facebook posts (*n* = 357,636), Instagram posts (*n* = 2,727) and original tweets (*n* =69,054). (See Table 1 below). Data collection and analysis method, which will be described below, complied with the terms and conditions of the sources of data, i.e., Twitter and Facebook.

Table 1 - *Breakdown of the datasets used for statistical analyses*

TYPE	Facebook	Twitter	Instagram
Pro-AKP media	516,863	66,960	28,780
Liberal-Kemalist media	347,466	29,838	25,791
Ulusalcı media	357,636	69,054	2,727

Following Rathje et al (2021), I used R package "quanteda" to analyze text from Twitter, Facebook and Instagram. During text preprocessing, we removed punctuation, URLs, and numbers. To categorize the data for analysis, I focused on four topic areas, namely: Pro-AKP, Liberal-Kemalist, Moral-emotional and the GM. And in classifying whether a specific post was referring to any of these topic areas, I created dictionaries for each of them. Specifically, these dictionaries included 1) *Pro-AKP dictionary*: a list of the most famous politicians from the People's Alliance (which is comprised by the governing AKP and the Nationalist Movement Party- MHP), along with their Twitter handles (e.g., "Erdoğan," "Bahçeli," "@RTErdoğan" or "@dbdevletbahceli) and a list of 21 words associated with Conservative Identity ; 2*) Liberal-Kemalist dictionary*: a list of the most famous politicians from the opposition's Nation's Alliance (which consists of four parties including the main opposition party, Republican People's Party- CHP), most famous politicians from Democracy and Enterprise Party (Deva) and Future Party, along with their Twitter handles (e.g., "Kılıçdaroğlu," "Meral Akşener", "@alibabacan", "@ Ahmet_Davutoglu") and a list of about 15 terms associated with Liberal Identity (e.g., "liberal," "democrat," or "leftist"); 3) *Moral-emotional dictionary*: a list of moral-emotional words adapted from previously validated dictionaries in other studies (Brady et al, 2019) (e.g., "agitate," "abuse," "honor," "honest", etc.); and 4) *Gülen-Movement dictionary*: a list of words commonly used to demonize the GM (e.g., "FETÖ", "traitor," "assassin," "slug", etc.), along with the twitter handles of popular individuals associated with the movement (e.g., "@FGülencomTR," "@ekremdumanli," "@EnesFreedom"). Examples of demonizing tweets, and Facebook and Instagram posts from the foregoing datasets about the GM can be found in Table 2 below. In creating these dictionaries, I benefited from various text analyses including uni-grams, bi-grams and topic models, which can be found in SI Appendix, Figs. 3-5. All dictionaries are in Turkish and available on the OSF, along with the datasets and the R-script code file (https://osf.io/q9yp5/).

Table 2 - *Sample Tweets and Facebook & Instagram Messages*

Dataset	Text	Retweet/ Share Count
Pro-AKP Media		
Facebook	Don't let the vehicles of **parallel's** Sürat Cargo enter Istanbul	8,062
Instagram	People flocked to the 15 July Martyr's Bridge. President Recep Tayyip Erdogan addressed citizens here: "We have **cut** the **arms of the octopus** grown by the **damned** [referring to Gulen] in **Pennsylvania**, let it be known like this! He added, "We will pursue our struggle until the last **Fetoist** is brought to account."	8,030
Twitter	Homeland is sacred, watch duty is sacred! Don't leave the homeland to **traitors**! #WeAreInSquaresInStateOfEmergency	1,414
Liberal-Kemalist Media		
Facebook	We know best what **skunk** the **jamaat** is, it should be **scraped** and **erased**, that's ok, but… Patient pays the price…doctor pays the price… teacher pays the price…child pays the price… governor pays the price…parents pay the price…dialysis machine pays the price…x-ray machine pays the price…	22,654
Instagram	A response to Erdogan by Imamoglu with 'period.' The elected mayor of Istanbul Imamoglu responded to the President Recep Tayyip Erdogan who said "Data examination is a **FETO tactic**" by saying "I did not appear on Samanyolu TV to solicit donations, didn't do any opening. Ask them to refresh their memories. A 'period' to this too!"	33,271
Twitter	#IfSozcuIsSilentTurkeyIsSilent 10 years ago, when you were calling **Fethullah** "Reverend," we were calling them **FETO**!	1,004
Ulusalcı Media		
Facebook	Wives of **putschist bastards** are booty!	358
Instagram	---- -----, the **fugitive FETOist** businessman whom Turkey demanded from England made the expected explanation today. ----, who spoke to **fugitive FETOist** ----- ----- on his Youtube channel, responded to -----'s questions…	1,705
Twitter	**Death threat** on live TV by --------, whose ex-husband had once hosted a program on **FETO's** closed-down -------- TV: "If there is another coup, my family will **take care of [kill]** 50 people"	353

* All posts are in Turkish, which are translated by the author, whose native language is Turkish

In each dataset, adapting prior methods (Brady et al., 2019; Rathje et al., 2021), I fit ordinary least squares regression models to examine how language about the Pro-AKP, language about the Liberal-Kemalist, language about the GM, as well as moral-emotional language predicted shares and retweet rates. I controlled for whether a post contained a URL, media (i.e., photo or video), and the number of followers each account had. All variables were mean-centered using the R package "jtools." Following the abovementioned work, I also log-transformed the retweet-count in Twitter datasets and total interactions outcome variables in Facebook and Instagram datasets given that these variables are usually skewed. Afterward, I conducted cluster-robust standard error analyses using the R package "miceadds." Analyses were performed using R version 4.1.2.

4. Results

To test my hypothesis, I analyzed a sizable volume of messages posted on Facebook, Twitter, and Instagram (n = 1,445,115) by the official accounts of the aforementioned three types of media. (For more information, see *Data and Methods* section and Table 1). I will present the results for each media type separately.

Study 1: Pro-AKP media

In Study 1, I first looked at the effects of moral-emotional language on three types of datasets. Controlling for all other variables, each additional moral-emotional word was associated with 10% increase on retweet rates, had no effect on Facebook posts, while on Instagram, it decreased shares by around 3% (exp(b) = 0.97, 95% CI = [0.95, 0.99], $p < 0.001$). Except for Twitter, these results are in contrast with prior work that demonstrate the moral contagion effect on social media (Brady et al., 2020; Rathje et al., 2021). Political in-group language was consistently associated with an increase in shares and retweets by around 19 to 55% across three datasets. Political out-group language was associated with a slight increase in shares by around 2% and 12% in Facebook and Instagram respectively, and a considerably high increase by around 50% in retweets. The results regarding partisan (in-group vs. out-group) language replicate previous research showing that "people selectively follow and retweet in-group members at much higher rates than out-group members" (Shin & Thorson, 2017; Mosleh et al., 2021).

Finally, to test my primary hypothesis, I looked at the demonizing language against the GM. In the Facebook dataset, each additional word about the GM was associated with an increase in shares by around 53% (exp(b)

= 1.53, 95% CI = [1.50, 1.56], $p < 0.001$), which is notable given that the increasing effect is almost equal to political in-group language (i.e., 55%). This effect was similar on Twitter and Instagram, as it led to an increase in retweets and shares by 25% (exp(b) = 1.25, 95% CI = [1.19, 1.31], $p < 0.001$) and 21% (exp(b) = 1.21, 95% CI = [1.15, 1.28], $p < 0.001$), respectively. The full regression models are reported in SI Appendix, **Table S1** and are plotted visually in Fig.1.

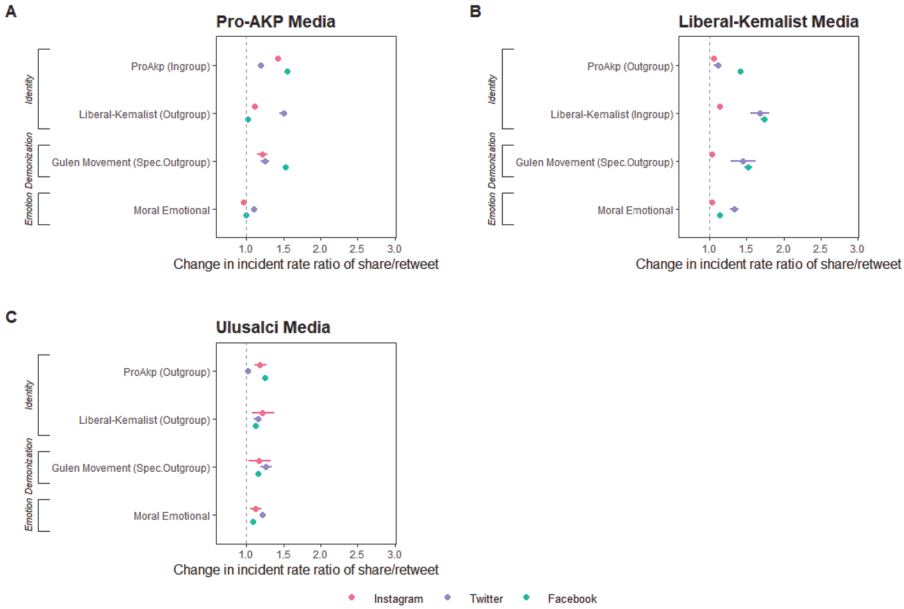
The results were similar when the models were rerun with cluster-robust SEs with each media account representing a different cluster (SI Appendix, **Table S3**). To further probe the importance of each predictor in the model, I calculated a relative importance analysis (SI Appendix, **Table S10**). In Facebook and Twitter datasets, words related to the GM had "lmg" values (an estimate of the R2 contributed by each predictor) parallel to its beta values in the regression models, except for the Instagram dataset where "lmg" values of GM was the lowest. Taken together, it is justified that demonizing language against the GM was a significant predictor of virality in Pro-AKP media's messages on Facebook, Twitter and Instagram.

Study 2: Liberal-Kemalist media

In Study 2, I also first looked at the effects of moral-emotional language on three types of datasets. Controlling for all other variables, each additional moral-emotional word was associated with 4 to 34% increase in shares and retweets. Political out-group language was associated with increase in shares and retweets by around 6 to 42% across three datasets. Political in-group language was consistently associated with an increase in shares and retweets by around 14 to 74% across three datasets, Facebook being the highest (exp(b) = 1,74, 95% CI = [1.69, 1.79], $p < 0.001$). Similar to Pro-AKP media, these results are consistent with studies proposing that in-group language is the strongest predictor of diffusion on social media.

Finally, in the Facebook dataset, each additional word about the GM was associated with an increase in shares by around 52% (exp(b) = 1.52, 95% CI = [1.47, 1.58], $p < 0.001$). This effect was similar on Twitter, as it led to an increase in retweets by 45% (exp(b) = 1.45, 95% CI = [1.29, 1.63], $p < 0.001$) and a slight increase on Instagram by 4% (exp(b) = 1.04, 95% CI = [1.01, 1.07], $p < 0.001$). respectively. The full regression models are reported in SI Appendix, **Table S4** and are plotted visually in Fig.1.

Figure 1 - *Full regression models in three social media platforms*



Similar to Study 1, the results were similar when the models were rerun with cluster-robust SEs with each media account representing a different cluster (SI Appendix, **Table S6**). To further probe the importance of each predictor in the model, I calculated a relative importance analysis (SI Appendix, **Table S11**). In Facebook and Instagram datasets, words related to the GM had "lmg" values (an estimate of the R2 contributed by each predictor) parallel to its beta values in the regression models, except for the Twitter dataset where "lmg" values of GM was the third highest among four variables (dictionaries) compared to its beta coefficient in the regression model, which was the second highest. Thus, like the Pro-AKP media, it is justified that demonizing language against the GM was a significant predictor of virality in Liberal-Kemalist media's messages on Facebook, Twitter and Instagram.

Study 3: Ulusalcı Media

In Study 3, I also first looked at the effects of moral-emotional language on three types of datasets. Controlling for all other variables, each additional moral-emotional word was associated with 8 to 22% increase in shares and retweets. For Ulusalcı media, all groups are out-group, except for the Pro-AKP which the former supports in certain aspects, as mentioned above. As such, Pro-AKP language was associated with an increase in shares and retweets by around 02 to 26% across three datasets, Facebook being having the highest (exp(b) = 1.26, 95% CI = [1.24, 1.28], $p < 0.001$). Liberal-Kemalist language was associated with increase in shares and retweets by around 12 to 22% across three datasets, this time Instagram having the highest (exp(b) = 1.22, 95% CI = [1.07, 1.38], $p < 0.001$).

As per the demonizing language against the GM, each additional word about the GM in the Facebook dataset was associated with an increase in shares by around 15% (exp(b) = 1.15, 95% CI = [1.12, 1.18], $p < 0.001$) and on Instagram by 18% (exp(b) = 1.18, 95% CI = [1.04, 1.33], $p < 0.001$), respectively. This effect was higher on Twitter, as it led to an increase in retweets by 26% (exp(b) = 1.26, 95% CI = [1.19, 1.34], $p < 0.001$). The full regression models are reported in SI Appendix, **Table S7** and are plotted visually in Fig.1.

Similar to Studies 1 and 2, the results were similar when the models were rerun with cluster-robust SEs with each media account representing a different cluster (SI Appendix, **Table S9**). To further probe the importance of each predictor in the model, I calculated a relative importance analysis (SI Appendix, **Table S12**). In Facebook dataset, words related to the GM had "lmg" values parallel to its beta values in the regression models, while in the Instagram dataset "lmg" values of GM was slightly lower than the other variables and in the Twitter dataset it was the second highest among four variables (dictionaries) whereas its beta coefficient had the highest score in the regression model. Taken together, despite slight differences in terms of relative importances, our results show that demonizing language against the GM was a significant predictor of virality in Ulusalcı media's messages on Facebook, Twitter and Instagram.

5. Additional analyses: Regressions with 'identity words' only and effect sizes

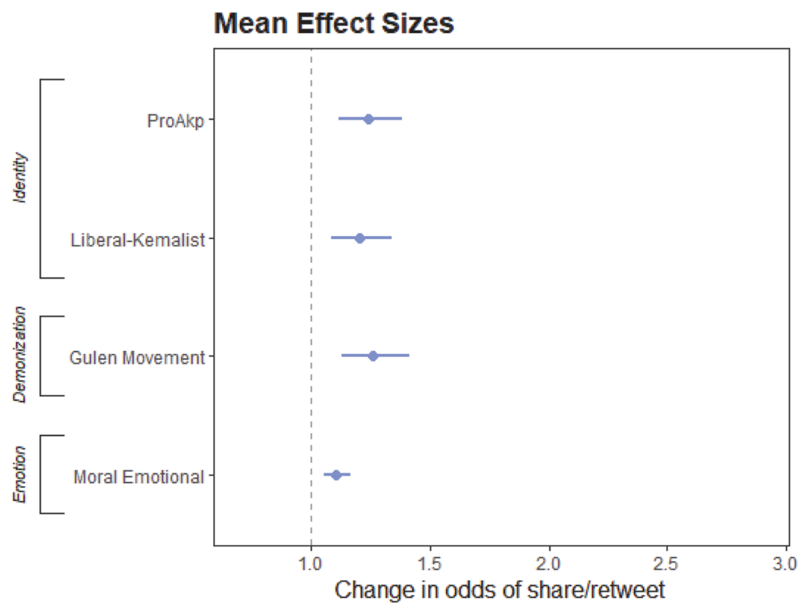
I wanted to understand whether the effect of GM words was not driven by any specific words, particularly "Gülen," "Fethullah," "Erdoğan," etc. To test this, I removed names and account names of persons from dictionaries and retained only identity terms such as "FETÖ," "traitor," "slug," etc. New regression models yielded similar results to the original models. As our focus is on demonizing speech, looking only at the 'identity' terms, language about the GM led to an increase from 13 to 52% in shares on Facebook and an increase from 5 to 22% on Instagram. On Twitter, an additional word about the GM increased retweets from 21 to 39%. A comparison of regression results with and without identity words related to GM is provided below in Table 3 below.

Table 3 - *Comparison of beta coefficients for the GM (Original dictionaries vs. Identity words only)*

TYPE	Facebook Original	Facebook (Identity words only)	Instagram Original	Instagram (Identity words only)	Twitter Original	Twitter (Identity words only)
Pro-AKP media	1.53	1.52	1.21	1.22	1.25	1.23
Liberal-Kemalist media	1.52	1.48	1.04	1.05	1.45	1.39
Ulusalcı media	1.15	1.13	1.18	1.17	1.26	1.21

Furthermore, following prior work (Rathje et al., 2021), I wanted to estimate the average effect sizes across all nine datasets. To this end, I conducted a series of internal meta-analysis (Fig.2 and SI Appendix, Table S13), in which I computed random-effects due to my expectation that this effect would vary in different contexts and used Dersimonian-Laird estimator. Across datasets, demonization language had the largest effect size, in that each word related to the GM increased the estimated percent increase of a share or retweet by about 26% (estimated exp(b) = 1.26, 95% CI = [1.12, 1.41], $p < 0.001$). Similarly, each Pro-AKP word increased the estimated percent increase of a share or retweet by about 24% (estimated exp(b) = 1.24, 95% CI = [1.11, 1.38], $p < 0.001$), whereas for Liberal-Kemalist language this effect was about 20% (estimated exp(b) = 1.24, 95% CI = [1.08, 1.33], $p < 0.001$). Moral-emotional language had the lowest effect size of about 10% (estimated exp(b) = 1.10, 95% CI = [1.05, 1.16], $p < 0.001$).

Figure 2 - *Mean effect sizes across nine datasets*



Put differently, the average percent increase in shares of demonizing language against the GM was about 2.5 times as large as that of moral emotional langauge. This finding is noteworthy because moral emotional language is a well-established predictor of diffusion on social media platforms. In addition, the effect of demonizing language was about 1.08 times as large as that of Pro-AKP language and 1.3 times as large as that of Liberal-Kemalist language. It is also notable that demonization language had larger effect size across all nine datasets than the Pro-AKP and Liberal-Kemalist words, or (depending on the media type analyzed) in-group or out-group words, which are also well-established predictors of engagement or virality on social media.

6. Discussion: General vs. specific out-group language

The results of this study point to another unexplored dynamic in terms of understanding virality on social media, i.e., the difference between the general and specific out-group language. Considering the Turkish socio-political context, this research used the terms in-group and out-group in general terms. For pro-AKP people, for example, Liberal-Kemalists are the main out-group; whereas for the latter, religiously conservative people, a big portion of whom are pro-AKP, constitute the out-group. To reflect this, and as it was explicated earlier, I created dictionaries by including general terms about these groups, such as most influential individuals and identity words representing their ideological positions. In light of this, it will not be erroneous to posit that the GM manifests itself as a specific out-group for the majority of groups in Turkey's social fabric, largely due to the demonization it has been subjected to especially during the last decade, among other things. Rereading the findings of this study therefore yields notable results on the distinction between general and specific out-group language in relation to their effect on engagement or virality on social media.

In Pro-AKP media, each additional general out-group word (i.e., Liberal-Kemalist) on Facebook was associated with a slight increase in shares by around 2%, whereas language about the specific out-group (the GM) increased shares by 53%, (exp(b) = 1.53, 95% CI = [1.50, 1.56], $p < 0.001$). On Instagram, specific out-group language increased shares by 21%, compared to general out-group language, which was 12%. Only on Twitter, this relationship was reversed, given that general out-group language increased retweets by 50%, (exp(b) = 1.50, 95% CI = [1.45, 1.55], $p < 0.001$), while the specific out-group language led to an increase in retweets by 25%. In Liberal-Kemalist media, each additional specific out-group word (the GM) increased shares by 52%, (exp(b) = 1.52, 95% CI = [1.47, 1.58], $p < 0.001$), whereas the language about the general out-group (i.e., Pro-AKP) led to an increase in shares by 42%. On Instagram, the effect of the two languages on shares was close, as general out-group language led to an increase by 6% and specific out-group language by 4%. On Twitter, specific out-group language increased retweets by 45%, ($\exp(b) = 1.45$, 95% CI = [1.29, 1.63], $p < 0.001$), whereas general out-group language increased retweet by around 11%. (For comparative regression coefficients, see Table 4 below). The foregoing comparisons could not be made regarding Ulusalcı media, for the concepts of out-group and in-group cannot be applied to them in the same fashion as the other media. As mentioned before, this is largely linked to shifting ideological stances and priorities of Ulusalcı groups, in addition to the compartmentalized nature of their political alignments.

Table 4 - *Regression results: General out-group language vs. Specific out-group language*

TYPE	Facebook		Instagram		Twitter	
	General out-group language	Specific out-group language (The GM)	General out-group language	Specific out-group language (The GM)	General out-group language	Specific out-group language (The GM)
Pro-AKP media	1.02	**1.53**	1.12	**1.21**	1.50	1.25
Liberal-Kemalist media	1.42	**1.52**	1.06	1.04	1.11	**1.45**

All in all, in the four of the six datasets from Pro-AKP media and Liberal-Kemalist media, the estimated percent increase of specific out-group language were significantly higher than that of general out-group language.

7. Conclusion

This study has sought to explore the impact of hate speech on virality on social media by using a case study from Turkey, i.e., The Gülen Movement (GM). As explicated, due to a series of events that turned one-time-friends (AKP and the GM) into enemies. The movement was socially, politically and discursively constructed by the Erdogan regime as a terrorist organization, and demonizing language about the movement, or anybody deemed to be affiliated with it, became a standard in gauging citizens' loyalty to the State, having myriad social, political and legal ramifications. That is why, this study expected that hate speech in the form of demonizing language about the GM would have a significant impact on diffusion or virality on Turkey's social media ecosystem.

The study results show that demonizing language against the GM is a significant predictor of virality in Turkey's social media ecosystem, namely:

Facebook, Instagram and Twitter. The results also show that demonizing language has the largest effect size compared to other well-established predictors of virality such as the moral-emotional language, language about the in-group and language about the out-group. In addition, reinterpreting the study results in a different way by differentiating between the general out-group language *versus* specific out-group language yielded interesting results. In four of the six datasets from pro-AKP and Liberal-Kemalist media, each additional specific out-group (the GM) word led to significantly higher increases in shares and retweets than a general out-group (pro-AKP or Liberal-Kemalist) word. In one dataset (Liberal-Kemalist media/Instagram), the results were quite close, while only in one dataset (pro-AKP media/Twitter), the estimated percent increase of general out-group language to be retweeted were significantly higher than the specific out-group language. It would be quite interesting to see whether the same distinction would bring about similar results for the general in-group language *versus* specific in-group language, a topic worthy of exploring in future research.

Lastly, social media platforms claim to do good for people in various ways. For instance, Facebook's mission statement reads, "to give people the power to build community and bring the world closer together" (Facebook, 2021). Similarly, Twitter espouses to "foster free and global conversations" and it claims to be "committed to healthy discourse" (Twitter, 2022). These findings of this research demonstrate that, while providing people with a space for free speech and connecting people together, social media platforms may be enabling users with malicious intent, such as spreading and promoting hateful, demonizing speech against a certain group of people. As such, this study may be useful for social media platforms in terms of reassessing their policies on content moderation. They can also investigate why some specific out-group words lead to higher diffusion in their platforms than general out-group words. These, in turn, have important implications for Countering Violent Extremism (CVE) given that victims of hate speech on social media platforms (in this study, people affiliated with the Gülen movement) are particularly susceptible to radicalization. Future research in this area will also be helpful and justified.

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Supplementary Information for
This file includes:

Table S1 - *Full Regression Models for Study 1*

	Pro-AKP Media		
	Facebook	Instagram	Twitter
Intercept	25.27***	675.12***	5.31***
	[25.07, 25.46]	[667.74, 682.58]	[5.08,5.55]
Gulen_Mov	1.53***	1.21***	1.25***
	[1.50, 1.56]	[1.15,1.28]	[1.19,1.31]
ProAKP	1.55***	1.42***	1.19***
	[1.53, 1.58]	[1.38,1.46]	[1.17,1.21]
MoralEmotional	1.00 n.s	0.97***	1.10***
	[0.99, 1.01]	[0.95,0.99]	[1.08,1.12]
LibKem	1.02 n.s	1.12***	1.50***
	[0.99, 1.05]	[1.07,1.16]	[1.45,1.55]
has_mediaTRUE	1.74***		
	[1.72,1.75]		
has_URLSTRUE			0.60***
			[0.57,0.62]
followers_c	1.20***	2.82***	1.30***
	[1.19,1.21]	[2.78,2.85]	[1.30,1.31]
N	516,863	21,096	66,960
AIC	2089674.01	51217.29	177056.19
BIC	2089763.25	51271.98	177129.08
Pseudo R^2	0.04	0.60	0.16

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table S2 - *VIFs for Study 1*

Pro-AKP Media			
	Facebook	Instagram	Twitter
	VIF	VIF	VIF
Gulen_Mov	1.00	1.01	1.00
ProAKP	1.00	1.01	1.05
MoralEmotional	1.00	1.01	1.00
LibKem	1.00	1.01	1.00
has_URLTRUE			1.02
has_mediaTRUE	1.13		
followers_c	1.12	1.01	1.07

Note. Variance Inflation Factors (VIFS) for study 1.

Table S3 - *Study 1 Robustness Check (Cluster Robust Standard Errors)*

	Pro-AKP Media		
	Facebook	Instagram	Twitter
Intercept	25.27***	675.12***	5.31***
	[25.07, 25.46]	[667.74, 682.58]	[5.01,5.62]
Gulen_Mov	1.53***	1.21***	1.25***
	[1.50, 1.56]	[1.12,1.32]	[1.19,1.31]
ProAKP	1.55***	1.42***	1.19***
	[1.53, 1.58]	[1.37,1.48]	[1.17,1.21]
MoralEmotional	1.00 n.s	0.97***	1.10***
	[0.99, 1.01]	[0.95,0.99]	[1.08,1.12]
LibKem	1.02 n.s	1.12***	1.50***
	[0.99, 1.05]	[1.07,1.17]	[1.44,1.57]
has_mediaTRUE	1.74***		
	[1.72,1.75]		
has_URLSTRUE			0.60***
			[0.56,0.63]
followers_c	1.20***	2.82***	1.30***
	[1.19,1.21]	[2.78,2.85]	[1.30,1.31]
N	516,863	21,096	66,960
AIC	2089674.01	51217.29	177056.19
BIC	2089763.25	51271.98	177129.08
Pseudo R^2	0.04	0.60	0.16

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table S4 - *Full Regression Models for Study 2*

	Liberal-Kemalist Media		
	Facebook	Instagram	Twitter
Intercept	78.90***	3403.92***	11.96***
	[77.57, 80.25]	[3365.02, 3443.27]	[11.27,12.68]
Gulen_Mov	1.52***	1.04***	1.45***
	[1.47, 1.58]	[1.01,1.07]	[1.29,1.63]
ProAKP	1.42***	1.06***	1.11***
	[1.40, 1.45]	[1.04,1.07]	[1.07,1.16]
MoralEmotional	1.14***	1.04***	1.34***
	[1.12, 1.16]	[1.02,1.05]	[1.28,1.40]
LibKem	1.74***	1.14***	1.68***
	[1.69, 1.79]	[1.12,1.17]	[1.55,1.81]
has_mediaTRUE	1.35***		
	[1.32,1.37]		
has_URLSTRUE			1.13***
			[1.07,1.20]
followers_c	6.72***	1.75***	0.00***
	[6.63,6.82]	[1.72,1.77]	[0.00,0.00]
N	347,466	25,791	29,838
AIC	1319509.26	70103.93	104256.36
BIC	1319595.33	70161.04	104322.79
Pseudo R^2	0.19	0.20	0.02

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table S5 - *VIFs for Study 2*

Liberal-Kemalist Media			
	Facebook	Instagram	Twitter
	VIF	VIF	VIF
Gulen_Mov	1.00	1.05	1.01
ProAKP	1.01	1.04	1.03
MoralEmotional	1.00	1.05	1.01
LibKem	1.00	1.02	1.00
has_URLTRUE			1.02
has_mediaTRUE	1.00		
followers_c	1.01	1.03	1.01

Note. Variance Inflation Factors (VIFS) for study 2.

Table S6 - *Study 2 Robustness Check (Cluster Robust Standard Errors)*

Liberal-Kemalist Media			
	Facebook	Instagram	Twitter
Intercept	78.90***	3403.92***	11.96***
	[77.59, 80.23]	[3365.02, 3443.27]	[11.28,12.67]
Gulen_Mov	1.52***	1.04***	1.45***
	[1.47, 1.58]	[1.02,1.07]	[1.28,1.64]
ProAKP	1.42***	1.06***	1.11***
	[1.39, 1.45]	[1.05,1.07]	[1.06,1.17]
MoralEmotional	1.14***	1.04***	1.34***
	[1.12, 1.16]	[1.03,1.05]	[1.29,1.40]
LibKem	1.74	1.14***	1.68***
	[1.66, 1.82]	[1.12,1.17]	[1.54,1.82]
has_mediaTRUE	1.35***		
	[1.33,1.37]		
has_URLSTRUE			1.13***
			[1.07,1.20]
followers_c	6.72***	1.75***	0.00***
	[6.64,6.81]	[1.72,1.77]	[0.00,0.00]
N	347,466	25,791	29,838
AIC	1319509.26	70103.93	104256.36
BIC	1319595.33	70161.04	104322.79
Pseudo R^2	0.19	0.20	0.02

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table S7 - *Full Regression Models for Study 3*

Ulusalcı Media			
	Facebook	Instagram	Twitter
Intercept	11.60***	223.30***	4.48***
	[11.45,11.76]	[214.67, 232.28]	[4.40,4.56]
Gulen_Mov	1.15***	1.18**	1.26***
	[1.12, 1.18]	[1.04,1.33]	[1.19,1.34]
ProAKP	1.26***	1.19***	1.02 ns
	[1.24, 1.28]	[1.11,1.27]	[1.00,1.04]
MoralEmotional	1.08***	1.13***	1.22***
	[1.07, 1.10]	[1.05,1.21]	[1.19,1.24]
LibKem	1.12***	1.22***	1.15***
	[1.09, 1.16]	[1.07,1.38]	[1.10,1.21]
has_mediaTRUE	1.21***		
	[1.20,1.23]		
has_URLSTRUE			0.74***
			[0.73,0.76]
followers_c	1.02***		1.88***
	[1.01,1.03]		[1.85,1.91]
N	357,436	2,727	69,054
AIC	1258404.06	8011.05	193668.68
BIC	1258490.35	8046.52	193741.82
Pseudo R^2	0.01	0.02	0.09

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table S8 - *VIFs for Study 3*

Ulusalcı Media			
	Facebook	Instagram	Twitter
	VIF	VIF	VIF
Gulen_Mov	1.00	1.03	1.00
ProAKP	1.00	1.02	1.00
MoralEmotional	1.00	1.03	1.00
LibKem	1.00	1.01	1.00
has_URLTRUE			1.00
has_mediaTRUE	1.70		
followers_c	1.70		1.00

Note. Variance Inflation Factors (VIFS) for study 3.

Table S9 - *Study 3 Robustness Check (Cluster Robust Standard Errors)*

	Ulusalcı Media		
	Facebook	Instagram	Twitter
Intercept	11.60***	223.30***	4.48***
	[11.45,11.76]	[214.67, 232.28]	[4.39,4.57]
Gulen_Mov	1.15***	1.18**	1.26***
	[1.12, 1.18]	[1.05,1.31]	[1.19,1.34]
ProAKP	1.26***	1.19***	1.02 ns
	[1.24, 1.28]	[1.12,1.26]	[1.00,1.04]
MoralEmotional	1.08***	1.13***	1.22***
	[1.07, 1.10]	[1.05,1.21]	[1.19,1.24]
LibKem	1.12***	1.22***	1.15***
	[1.09, 1.16]	[1.08,1.37]	[1.10,1.21]
has_mediaTRUE	1.21***		
	[1.20,1.23]		
has_URLSTRUE			0.74***
			[0.73,0.76]
followers_c	1.02***		1.88***
	[1.01,1.03]		[1.85,1.91]
N	357,436	2,727	69,054
AIC	1258404.06	8011.05	193668.68
BIC	1258490.35	8046.52	193741.82
Pseudo R^2	0.01	0.02	0.09

*** p < 0.001; ** p < 0.01; * p < 0.05.

Table S10 - *Relative Importance Analysis for Study 1*

Pro-AKP Media			
	Facebook	Instagram	Twitter
Gulen_Mov	**0.07093**	**0.00052**	**0.00119**
ProAKP	0.14731	0.00741	0.01524
MoralEmotional	0.00096	0.00064	0.00097
LibKem	0.00053	0.00061	0.00567
has_URLTRUE			0.01180
has_mediaTRUE	0.60075		
followers_c	0.17948	0.56812	0.11475

Note. Note. “lmg” (or estimated R2) values are shown for each regression model

Table S11 - *Relative Importance Analysis for Study 2*

Liberal-Kemalist Media			
	Facebook	Instagram	Twitter
Gulen_Mov	**0.00105**	**0.00033**	**0.00151**
ProAKP	0.00271	0.00174	0.00056
MoralEmotional	0.00065	0.00064	0.00595
LibKem	0.00422	0.00427	0.00590
has_URLTRUE			0.00036
has_mediaTRUE	0.00184		
followers_c	0.17511	0.18340	0.00529

Note. Note. “lmg” (or estimated R2) values are shown for each regression model

Table S12 - *Relative Importance Analysis for Study 3*

Ulusalci Media			
	Facebook	Instagram	Twitter
Gulen_Mov	**0.00032**	**0.00358**	**0.00104**
ProAKP	0.00222	0.00979	0.00007
MoralEmotional	0.00034	0.00505	0.00480
LibKem	0.00019	0.00423	0.00056
has_URLTRUE			0.01064
has_mediaTRUE	0.00263		
followers_c	0.00112		0.06665

Note. Note. “lmg” (or estimated R2) values are shown for each regression model

Table S13 - *Meta-analysis of average effect sizes across nine datasets*

	Estimate	Conf.low	Conf.high
Gulen_Mov	1.26	1.12	1.41
ProAKP	1.24	1.11	1.38
LibKem	1.20	1.08	1.33
MoralEmotional	1.10	1.05	1.16

Figure S1 - *Volume of Facebook Page Posts containing the word "FETÖ": 2015-2022*

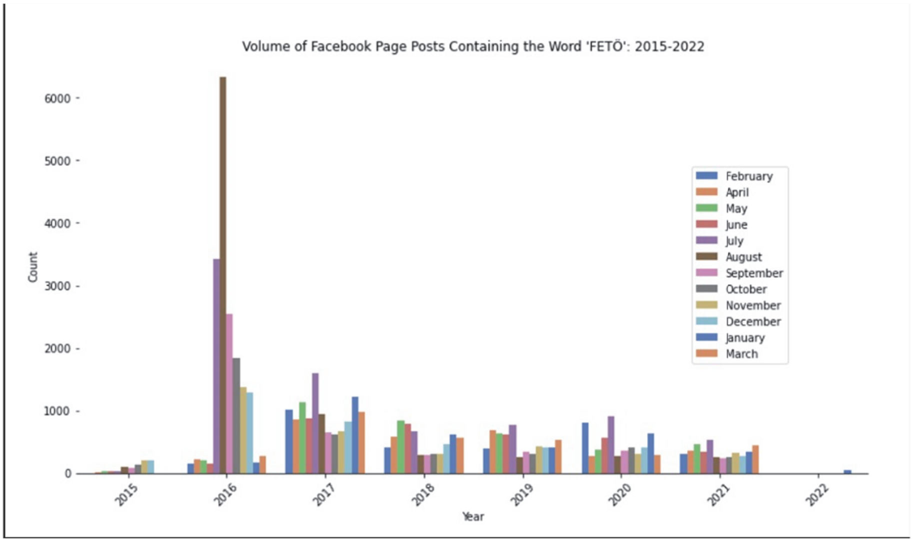


Figure S2 - *Community Detection Graph (FB Crowdtangle data) for Exploratory Data Analysis*

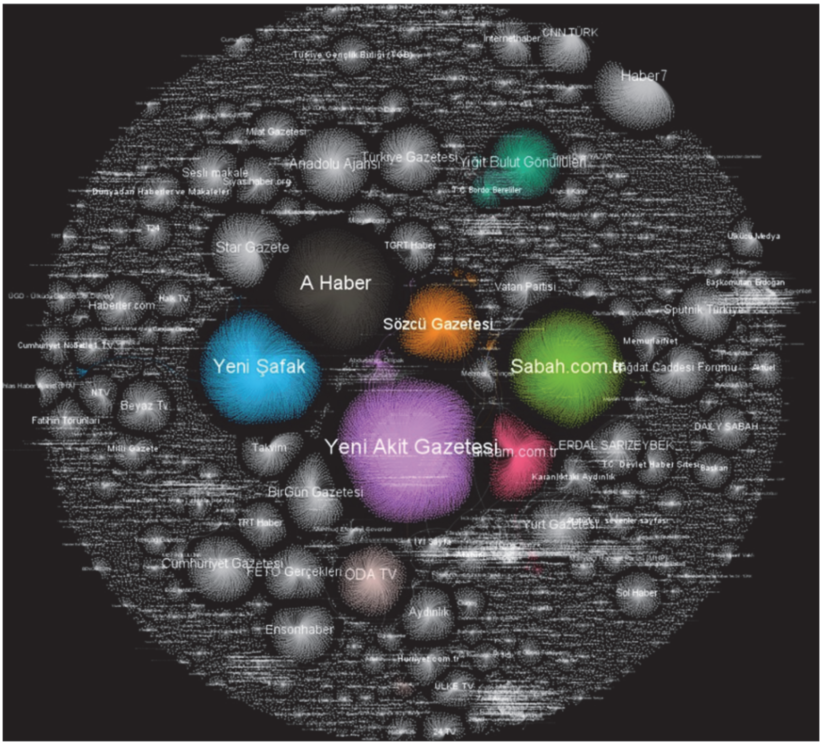


Figure S3 - *Top Bi-grams (word-pairs) for Exploratory Data Analysis (EDA)*

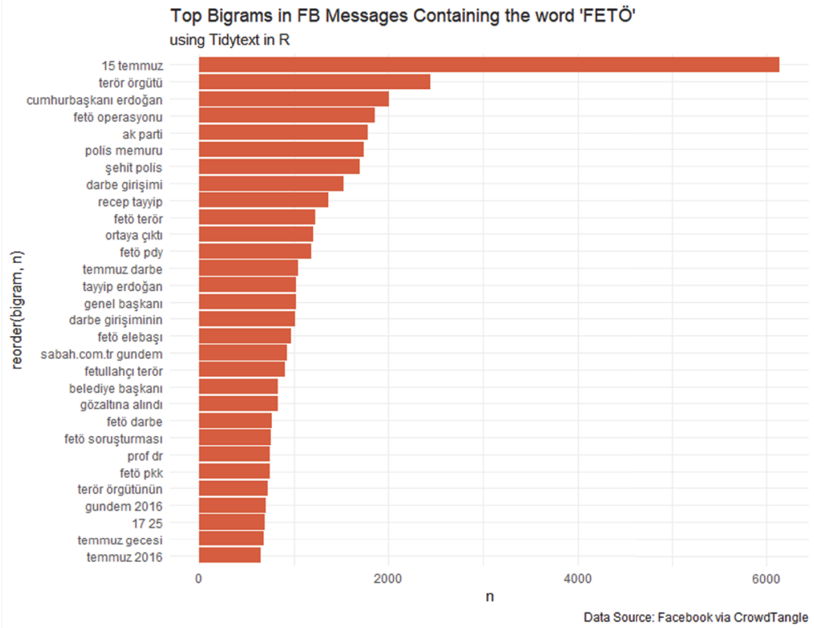


Figure S4 - *Top Uni-grams (single words) for Exploratory Data Analysis (EDA)*

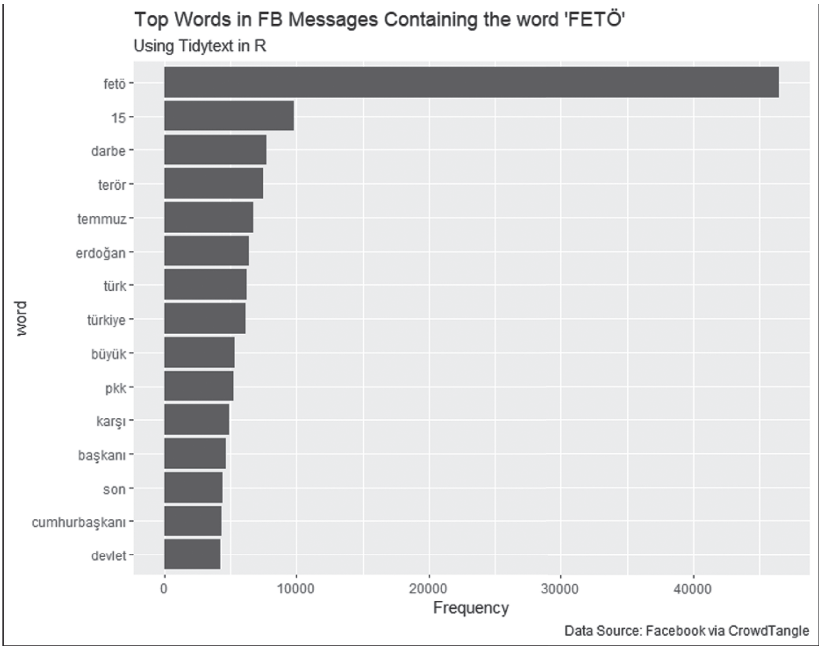
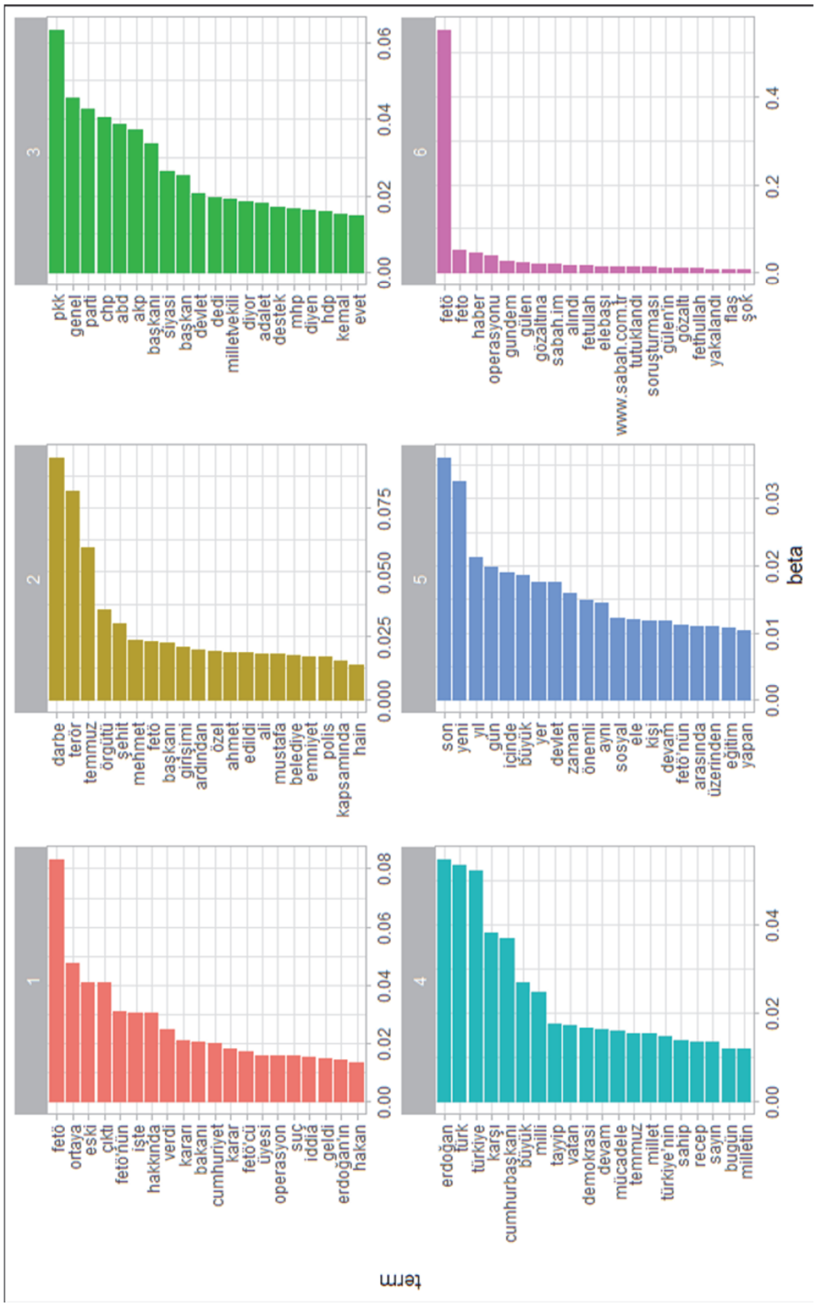


Figure S5 - *Topic models for Exploratory Data Analysis (EDA)*



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