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Verbal Aggression as an Indicator of Xenophobic Attitudes in Greek Twitter during and after the Financial Crisis

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Abstract

We present a replication of a data-driven and linguistically inspired Verbal Aggression analysis framework that was designed to examine Twitter verbal attacks against predefined target groups of interest as an indicator of xenophobic attitudes during the financial crisis in Greece, in particular during the period 2013-2016. The research goal in this paper is to re-examine Verbal Aggression as an indicator of xenophobic attitudes in Greek Twitter three years later, in order to trace possible changes regarding the main targets, the types and the content of the verbal attacks against the same targets in the post crisis era, given also the ongoing refugee crisis and the political landscape in Greece as it was shaped after the elections in 2019. The results indicate an interesting rearrangement of the main targets of the verbal attacks, while the content and the types of the attacks provide valuable insights about the way these targets are being framed as compared to the respective dominant perceptions and stereotypes about them during the period 2013-2016.

Keywords: Verbal Aggression, Xenophobia, Twitter

1. Introduction

Xenophobia is broadly defined as intense dislike, hatred or fear of those perceived to be strangers (Master and Roy, 2000). As a psychological state of hostility or fear towards outsiders (Reynolds and Vine, 1987), xenophobia is associated with feelings of dominance (implying superiority) or vulnerability (implying the perception of threat), respectively (Veer, 2013). As a disposition, xenophobia can be the basis of racism, fascism, and nationalism (Delanty and O'Mahony, 2002), since it is often rooted in (cultural, religious, racial, etc.) prejudices or driven by ideology.

Focusing mainly on the effects and the consequences of xenophobia in social life -rather than its conceptual formulation- Delanty and O'Mahony (2002) describe it as *rooted in the symbolic violence of everyday life*, while Bronwyn (2002) suggests that xenophobia is more than just an attitude towards foreigners; it can also take shape as a practice, and in particular as a violent practice. In this context, Verbal Aggression (VA) constitutes an important component in the study of xenophobia; aggressive messages targeting foreigners can be indicative of xenophobic attitudes. VA involves using messages to attack other people or those aspects of their lives that are extensions of their identity (Hamilton and Hample, 2011). The forms of aggression are manifold and vary from expressions of disgust and contempt, to threats, slander, insults, and hatred (Rȍsner and Krämer, 2016). The close relation of online VA with xenophobia is also demonstrated by the hate speech literature and especially by approaches that focus on xenophobia-related types of hate speech like racist (Kwok and Wang, 2013; Waseem and Hovy, 2016) and hate speech directed to immigrants (Sanguinetti et al., 2018) or to specific ethnic groups (Warner and Hirschberg, 2012), even though no explicit reference to xenophobia is made.

Traditionally, xenophobia is measured using data coming from focus groups, interviews, and public sentiment polls using standard questions in order to capture opinions, emotions, perceptions and beliefs (e.g. Eurobarometer). Despite the numerous research efforts in automatically detecting and analyzing online sentiment, VA and hate speech, user-generated content has been scarcely explored from the xenophobia measuring perspective in a large scale. A major up-to-date research effort that examined xenophobia as a violent practice using computational social science and big data techniques is the XENO@GR project[1]. Based on the research hypothesis that xenophobia is a deeply rooted social phenomenon that reasonably escalates under circumstances of severe economic crisis, the project aimed to examine whether (or not) xenophobia in Greece is an outcome of the financial crisis or it comprises a long-lasting social perception deeply rooted in the Greek society. This research puzzle was decomposed into specific Research Questions (RQs) and xenophobia was examined in terms of physical aggression (event analysis) and verbal aggression (VA) towards specific Target Groups, as attested in two types of textual data, namely news and tweets, using data mining techniques. Focusing on VA, almost 4.5 million Tweets covering the period 2013-2016 were analyzed using a VA analysis framework that provided valuable insights regarding the main targets and types of the verbal attacks, and the main stereotypes and prejudices about the TGs of interest during the financial crisis, helping the political and social scientists to formulate adequate responses to the project's RQs (Pontiki, 2019; Pontiki, Papanikolaou, and Papageorgiou, 2018).

In this paper we present a replication of the VA analysis framework three years later; in 2019 Greece is in the post financial crisis era, but the refugee crisis is still ongoing. In addition, the centre-right party New Democracy has won the 2019 general election ousting the left-wing Prime Minister Alexis Tsipras, while Golden Dawn -a neo-Nazi party that evolved from a marginal group into Greece's third-largest party during the financial crisis- was knocked out of the Parliament, as a result of the last elections. The research goal is to examine if the VA analysis framework can trace any imprint of these changes on public beliefs

[1] Project Website: http://xenophobia.ilsp.gr/?lang=en

and attitudes expressed in Twitter about the specific TGs; the results indicate an interesting rearrangement of the main targets of the verbal attacks, while the content and the types of the attacks provide valuable insights regarding how these TGs are being framed as compared to the respective dominant stereotypes about them during the period 2013-2016.

The remainder of this paper is structured as follows. Section 2 provides an overview of the methodology and the VA analysis framework that was used for both periods. The results for the period 2013-2016 and for the year 2019 are presented in Sections 3 and 4, respectively. The paper concludes with a discussion on the main findings (Section 5), as well as on the contribution and the limitations of the proposed methodology (Section 6).

2. Methodology

This paper focuses on VA analysis; event analysis is not discussed here. The current section elaborates on the methodology applied for the analysis of Twitter data, aiming at the identification of verbal attacks against specific target groups. This methodology was designed initially in the framework of XENO@GR project and applied on data from the period 2013-2016 and subsequently re-applied on 2019 Twitter data, in order to examine possible shifts in xenophobic reactions in the country in the post-crisis era. Results of the first experiment are presented in Section 3 while results from the second experiment in Section 4.

Xenophobia is a complex social phenomenon that reflects a deep-rooted form of fear and hostility towards the other, who is perceived as a stranger to the group oneself belongs to. In the context of the XENO@GR project the notion of other was limited to people with other than Greek nationality or origin, and further restricted to the following ten predefined TGs of interest based on specific criteria (e.g. population of the specific ethnic groups in Greece, dominant prejudices in Greece about the specific groups): TG1: PAKISTANI, TG2: ALBANIANS, TG3: ROMANIANS, TG4: SYRIANS, TG5: MUSLIMS/ISLAM, TG6: JEWS, TG7: GERMANS, TG8: ROMA, TG9: IMMIGRANTS, TG0: REFUGEES. IMMIGRANTS and REFUGEES were considered as two generic TGs and examined separately due to the different connotations and implicatures of these two lexicalizations; the research hypothesis was that people framed as *immigrants* are more likely to receive xenophobic behaviors rather than those framed as *refugees*. In addition, there are legal protection differences between *immigrants* and *refugees*; refugees are specifically defined and protected by international law, particularly regarding refoulement.

The overall workflow for building the framework was a five-step process, including the creation of textual and lexical languages resources and Natural Language Processing (NLP) tools for their processing. Specifically: **A. Data Collection.** For each TG of interest relevant Tweets were retrieved using related queries/keywords e.g. *ισλάμ* (Islam). The search function in the database configuration was stemmed, so the queries returned also Tweets containing morphological variations of the selected keywords. A total of 4.490.572 Tweets was retrieved covering the period 2013-2016. Fig. 1 illustrates the per-year amount of Tweets for each TG. **B. Data Exploration**. Samples of the collected data were manually explored in order to identify different aspects of VA related to the predefined targets of interest. **C. Knowledge Representation**. Based on data observations and literature review findings, a linguistically-driven typology of VA messages was designed (2.1). **D. Computational Analysis.** The data was modelled using the appropriate resources and algorithms that were designed and implemented for the computational treatment of the VA framework (2.2). **E. Data Visualization**. The output, having been revised, was visualized in various ways making the analysis results explorable, comprehensible and interpretable with regard to the RQs under study.

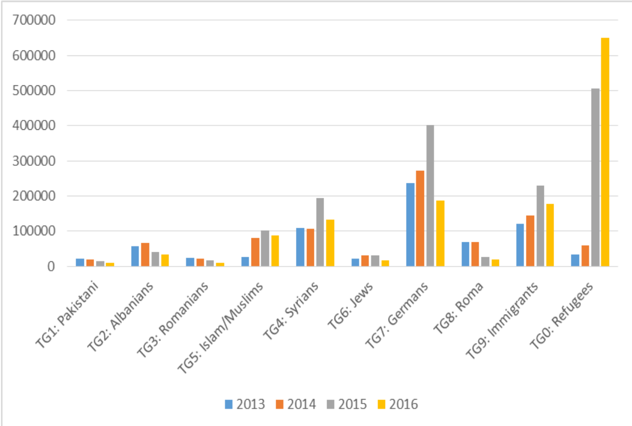

Figure 1: Amount of collected Tweets per year and TG.

2.1 Typology of VA Messages

Based on literature review and explorative analysis findings a linguistically-driven framework was developed where VA messages (VAMs) are classified based on: (a) their focus (distinguishing between utterances focusing on the target's attributes, and utterances focusing on the attacker's thoughts), (b) the type of linguistic weapon used for the attack, and (c) the content of the attack (e.g. threats/calls for physical violence or for deportation). The detailed typology is illustrated in Fig. 2 (Pontiki, 2019; Pontiki, Papanikolaou, and Papageorgiou, 2018).

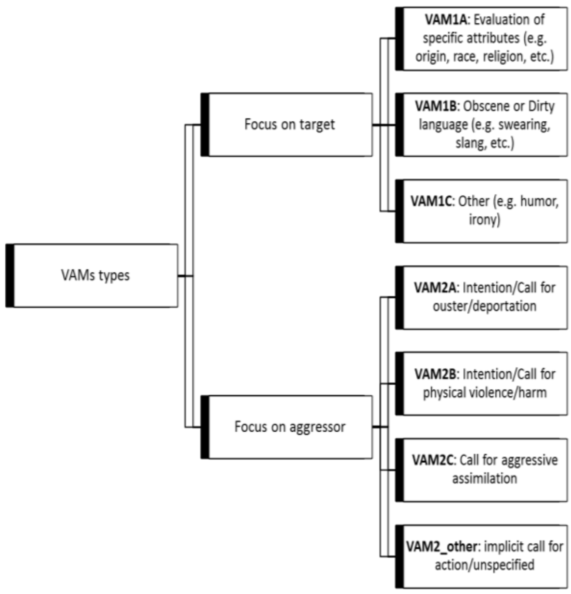

Figure 2: Typology of VAMs.

As illustrated above, two main types of VAMs are considered and further categorized in specific subtypes. (I) **VAM1.** Messages focusing on (the attributes of) the target (e.g. physical appearance, religion, etc.) further classified into subcategories based on the type of the linguistic devices (weapons) used by the aggressor to attack the target: formal evaluations of specific attributes (VAM1A), taboo or dirty language (VAM1B), and more complex linguistic devices such as humor or irony (VAM1C). (II) **VAM2.** Messages focusing on the aggressor's intentions providing information about specific types of attacks further classified into subcategories based on the content of the attack: intentions or calls for ouster/deportation -oriented to legal means- (VAM2A), intentions or calls for physical violence/harm -oriented to physical extinction- (VAM2B), calls for aggressive assimilation (VAM2C), and implicit or unspecified calls for action (VAM2D).

The typology was designed to provide both quantitative and qualitative information about the verbal attacks enabling to interpret VA as an indicator of xenophobic attitudes by addressing specific RQs based on the amount (main targets of the attacks), the type and the content (stereotypes and prejudices) of the aggressive messages.

2.2 VA Computational Framework

For the computational treatment of the above typology a linguistically-driven VA analyzer was designed. The approach is lexicon-based and explores shallow syntactic relations between aggressive terms (i.e. words that are used to express VA) and sequences of tokens-candidate targets of the attacks. The input is raw data. First, the data is processed through a NLP pipeline that performs tokenization, sentence splitting, part-of-speech tagging, and lemmatization using the ILSP suite of NLP tools for Greek (Papageorgiou et al., 2002; Prokopidis, Georgantopoulos and Papageorgiou, 2011), available through the CLARIN:EL infrastructure (https://www.clarin.gr/en), (Piperidis, Labropoulou, and Gavrilidou, 2017). Then, the analyzer detects candidate VAMs and targets based on the respective lexical resources. Finally, sets of grammars/ linguistic patterns determine which spotted candidate VAMs and targets are correct and classify them according to the typology.

The method is precision-oriented and focuses on explicitly stated VA; it relies on a set of lexical resources built to capture possible linguistic instantiations of VA towards the TGs of interest. VAMs that are instantiated through complex linguistic structures and devices (i.e. humor, implicit calls for action), and cannot be captured at the lexical level were considered out of scope. Exceptions were some specific cases of VAM1C and VAM2D that were found repeatedly in the data -reproducing some well-known stereotypes towards specific TGs- and were addressed using lexico-syntactic patterns. The performance of the VA analyzer was evaluated using a random selection of 500 Tweets per TG (5000 Tweets in total) in terms of Precision (84%), Recall (60%) and F-Measure (68%). Evaluation was performed also separately for each TG-specific sub-collection in order to obtain a more fine-grained and in-depth view of the results. More details about the VA framework and the experimental evaluation can be found in (Pontiki, 2019).

3. VA Analysis Findings for 2013-2016

The collected data (Fig.1) was processed using the VA analyzer. The output was recorded in a Knowledge Database (KD) and was, subsequently, used for statistical analysis and visualizations. For each processed Tweet, the KD was populated with two types of information: **A.** Annotations derived by the automatic VA analysis: TG_id (e.g. TG5), TG_evidence (the lexicalization of the TG as referred to in the Tweet e.g. *Ισλάμ* (Islam)), VAM_type (e.g. VAM1A), and VA_evidence (the lexicalization of the verbal attack as it appears in the Tweet e.g. *σκοταδισμός* (obscurantism)), and **B.** Twitter metadata: timestamp, User_id, and the Tweet text. A summary of the main findings with regard to the RQs under study is presented in the following sections.

3.1 Main Targets of Verbal Attacks

As illustrated above in Fig. 1, the most discussed TGs during 2013-2016 were REFUGEES and GERMANS. The peak in the mentions of REFUGEES during 2015-2016 coincides with the refugee crisis in Europe, whilst GERMANS were continuously in the limelight since, along with the IMF and the EU, the German Government had a central role in the Greek crisis. The next most discussed TGs were IMMIGRANTS and SYRIANS -also related with the refugee crisis-, and MUSLIMS/ISLAM, with a peak from 2014 onward which coincides with the rise of ISIS. However the number of Twitter mentions is not necessarily indicative of the amount of the verbal attacks against each TG. The VA analysis results (Fig. 3) indicate that the most mentioned TGs are not always the most attacked ones as well (e.g. REFUGEES were the most discussed but the least attacked TG).

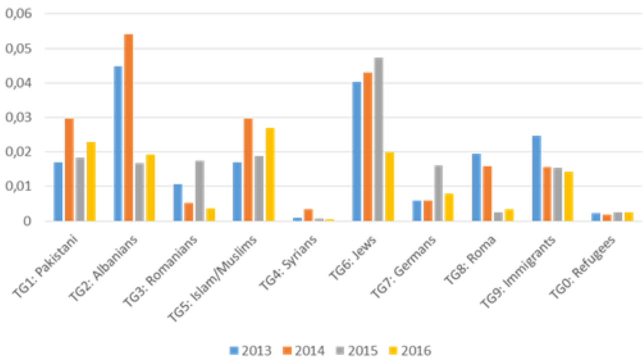

Figure 3: Per-year VA rate (VAMs/Tweets) per TG.

The most attacked TGs were JEWS, ALBANIANS, PAKISTANI, MUSLIMS/ISLAM, and IMMIGRANTS. Antisemitism appeared to be at the core of xenophobic discourse. This finding is in par with the findings of the ADL Global 100[2] survey, according to which Greece was the most anti-Semitic country in Europe -based on the strength of anti-Semitic stereotypes- scoring 69%. The role of anti-Semitism in the Greek political culture during that period had attracted attention after a series of opinion poll findings and most importantly after the rise of neo-Nazi Golden Dawn, a party with an explicit anti-Semitic discourse (Georgiadou, 2015).

[2] http://global100.adl.org/public/ADL-Global-100-Executive-Summary.pdf

ALBANIANS are perhaps the most established group of foreigners in Greek public discourse, given that the image of foreigner as it was constructed in Greece during and after the first wave of migration flow (early-mid 1990s) was mainly associated with Balkan -and mainly- Albanian nationality (Voulgaris et al., 1995). As for the generic group IMMIGRANTS, the results confirmed that it is more likely to verbally attack groups of people framed as IMMIGRANTS rather than as REFUGEES probably due to the different connotations/implicatures of these two lexicalizations. MUSLIMS have a long presence in Greece[3], however, the verbal attacks that targeted them were triggered by geopolitical events such as the rise of ISIS or events related to violent practices or sexual abuse of specific population groups (women, children). The information about the types and the content of attacks presented below provides interesting insights helping to better comprehend and interpret these findings.

3.2 Main Types of Verbal Attacks

The overall number of messages that express VA focusing on the target of the attack (VAM1) was quite bigger than the number of messages focusing on the aggressor's intentions (VAM2); the proportion of the detected VAMs of type 1 and 2 was approximately 89% and 11%, respectively. Focusing on VAM1 attacks, the TGs who were mostly attacked with messages negatively evaluating specific attributes of theirs (VAM1A) were ALBANIANS and JEWS, whilst PAKISTANI and IMMIGRANTS received the most obscene messages (VAM1B).

Focusing on VAM2 attacks, JEWS received most of them with ALBANIANS and PAKISTANI following in the second and third place, respectively (Fig. 8). In fact, calls for physical extinction (VAM2B) were much more for JEWS than for any other group. What needs to be noted is that there is not a significant number of JEWS living in Greece as compared to ALBANIANS and PAKISTANI that constitute the largest immigrant populations in this country. Moreover, aggressive messages related to JEWS reveal the emergence of threat perception based on biological and cultural terms, as well as the perception of a particular enmity towards the Greek nation (see also below 3.3). Threat perception seems to prevail also for PAKISTANI, ALBANIANS and IMMIGRANTS, according to the share of VAM2 attacks and, in particular, the calls for ouster/deportation (VAM2A) for the specific groups.

3.3 Stereotypes and Prejudices

Stereotypes and prejudices were examined focusing on the content of the verbal attacks. To this end, the linguistic evidence of the aggressive messages was visualized using word clouds containing the unique aggressive terms found per TG, based on the assumption that the unique linguistic weapons used against each TG may be associated with specific types of attributes or themes discussed per TG. The qualitative analysis of the results confirmed the existence of stereotypes and prejudices against specific TGs that are deeply rooted in Greek society. In the case of JEWS, the verbal attacks entailed a perception of a particular enmity towards the Greek nation and blame attribution patterns of the Greek crisis. As illustrated in Fig. 4, *εχθρότητα* (hostility) was the most frequent term tagging them. Common themes in this group of messages were the identification with the negative aspects of the banking system and global capitalism, as well as the frequent appeal to conspiracy theory elements e.g. *δολοπλόκος* (conniver), *διπλοπροσωπία* (double-faced), *καιροσκόπος* (opportunist), while Greece and banks were often tagged as *Εβραιοκρατούμενη* (owned by Jews). These findings are in par with the conclusions drawn from the survey of Antoniou et al. (2014) who established a correlation between conspiratorial thinking and ethnocentricism, and elaborated an interpretation of Greek anti-Semitism building on aspects of national identity and by employing the concept of victimhood. Another deeply rooted stereotype in Greek society that was reflected also in the verbal attacks against JEWS is the perception that they are avaricious e.g. *φραγκοφονιάς* (cheeseparing). Anti-Semitic attitudes entailed also notions of hate-speech e.g. the use of the term *σαπούνι* (soap) in a biting derogatory manner referring to soap made of Jewish victims by the Nazis.

Figure 4: Word Cloud of unique aggressive terms for JEWS.

A perception of a particular enmity towards the Greek nation was also dominant in the verbal attacks against GERMANS, who played a central role in the Greek crisis. The popularity of the anti-German attitudes in Greece was also attested by a series of public opinion findings (Pew Global Attitudes Project, 2012[4]). In the case of Twitter, a variety of evaluative terms were used to stress out the harshness and hostility of GERMANS against Greeks. Memories and symbols of WWII and of Nazi occupation of Greece were also instrumentalized in the context of this victimization repertoire. These findings suggested a resurgence of the anti-German narration in the context of the anti-austerity (anti-memorandum) discourse. Anti-German narration is considered to be the most prominent formulation of a victimization repertoire based on the foreign enemy concept and on the limited sovereignty discourse (Lialiouti and Bithymitris 2013).

The verbal attacks in the case of ALBANIANS and PAKISTANI entailed different perceptions; the dominant stereotypes in the construction of the image of ALBANIANS were associated with *crime* and *cultural inferiority* indicating a continuity of the so-called stereotype of the Balkanian criminal. The inferiority stereotype was also dominant for PAKISTANI; with the exception of some

[3] The Muslim minority in Thrace is the only officially recognized minority in Greece.

[4] https://www.pewresearch.org/global/2012/12/12/social-networking-popular-across-globe/pew-global-attitudes-project-technology-report-final-december-12-2012/

messages focusing on poor personal hygiene, physical appearance or the color of skin, PAKISTANI were mostly evaluated as inferior beings with derogatory morphological variations of their nationality name as a linguistic weapon. Crime and inferiority stereotypes were dominant also in the case of MUSLIMS/ISLAM, but with rather different aspects; the attacks were often lexicalized through evaluative and dysphemistic terms of insult or abuse to debase core Islamic values, practices, etc. indicating irrationalism, sexist behavior and fanaticism.

3.4 Discussion and Further Insights

The VA analysis framework designed in the context of the XENO@GR project provided valuable insights regarding the main targets and types of the verbal attacks, and the main stereotypes and prejudices about the TGs of interest during 2013-2016 helping the political and social scientists to address the project's RQs. According to these findings, xenophobia in Greece, when examined in terms of Twitter VA towards specific TGs of interest, seems to be culturally-rooted and not crisis-driven. The qualitative analysis of the aggressive messages argues in favor of a continuity of deeply rooted stereotypes about specific TGs (e.g. ALBANIANS, JEWS). However, the results indicate also the emergence of attacks that are associated with blame attribution patterns about the Greek crisis (e.g. GERMANS, JEWS). In other words, xenophobic attitudes may not be crisis-driven, but the economic crisis encourages the development of defensive nationalism and the perception of vulnerability. As for the refugee crisis that was in its peak during 2015-2016, its effect on public beliefs remained an open question for future research. The few verbal attacks that were captured against REFUGEES were mostly attempts to challenge their identity implying that they are illegal immigrants. This notion of illegality or lawlessness was also dominant in the case of IMMIGRANTS, who were mostly framed as *λαθρομετανάστες* and *λάθρο* (illegal).

The results illuminate also two different dimensions correlated to the conceptualization of xenophobia. On the one hand, attacks against TGs who are considered powerful (JEWS, GERMANS) are related to the concept of vulnerability, implying the perception of threat. As for the perception of vulnerability related to MUSLIMS/ISLAM, the attacks that entailed notions of Islamophobia were mostly triggered by the rise of ISIS and did not seem to constitute a core component of the Greek xenophobia, at least at that time period. On the other hand, dominance is directed against TGs thought of as inferior in socio-economic or cultural perspectives (ALBANIANS, PAKISTANI).

4. VA Analysis Findings for 2019

Following the same methodology as for the period 2013-2016, we retrieved relevant Tweets for each TG of interest. The search resulted in ten collections, which contain a total of 1.672.783 Tweets and cover the time period from 1/01/2019 until 31/12/2019. As it is illustrated in Fig. 5, REFUGEES, IMMIGRANTS, and SYRIANS continue to be in the limelight due to the ongoing refugee crisis. GERMANS, also remain a highly mentioned TG. The Tweets were processed with the same VA analysis framework used for the period 2013-2016.

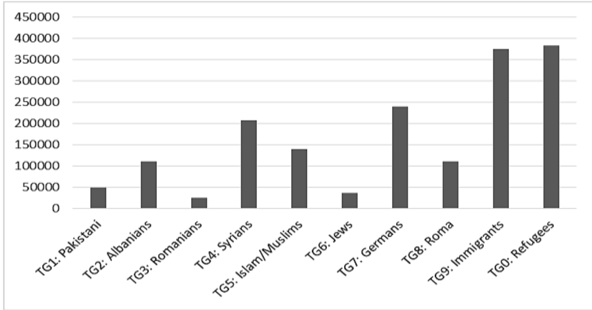

Figure 5: Amount of Tweets per TG for 2019.

4.1 Main Targets of Verbal Attacks

Fig. 6 illustrates the VA rate per TG for both periods enabling a direct comparison of the mostly attacked TGs during and after the financial crisis. Overall, the quantitative analysis of the verbal attacks indicates that xenophobic behaviors do not seem to be so dominant in Greek Twitter, since the VA rates (VAMs/Tweets) regarding the specific TGs in both periods are low (i.e. the VA rate for the mostly attacked TG is approx. 5%). Focusing on 2019, according to the results, the main targets are the same 5 TGs (JEWS, ALBANIANS, PAKISTANI, IMMIGRANTS and MUSLIMS/ISLAM) but they appear in different positions on the list. In particular, we observe an interesting shift of the two mostly attacked TGs during 2013-2016 (JEWS and ALBANIANS), to the 5th and 4th place, respectively, in 2019, and a respective elevation of PAKISTANI, IMMIGRANTS and MUSLIMS/ISLAM as the top three attacked TGs.

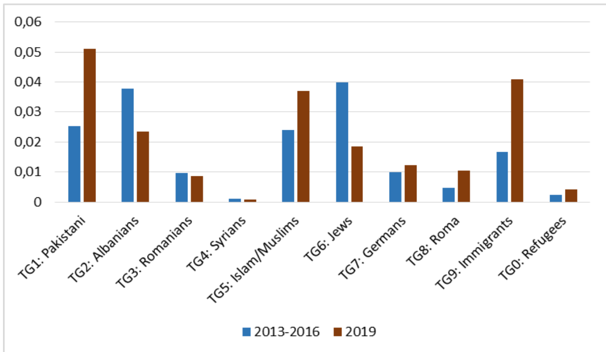

Figure 6: VA rate per TG and time period.

The fact that JEWS do not constitute the main target of the verbal attacks in the post crisis era seems to validate the findings during the crisis period; beside the culturally-rooted stereotypes, the verbal attacks against them entailed also blame attribution patterns about the Greek crisis and frequent appeal to conspiracy theory elements in the context of defensive nationalism and a perception of vulnerability. So, it could be argued that in the post crisis era, with the lessening of the feeling of vulnerability towards JEWS, the focus has been shifted to other groups who afflict the Greek society (PAKISTANI, IMMIGRANTS). This argument is also supported by the qualitative analysis of the content of the attacks (4.3).

Another important element that has to be taken into account in the interpretation of these results, is the weakening of the main source of anti-semitic discourse in Greece; the neo-Nazi party Golden Dawn has been framed as a criminal organization with its leadership being accused of a number of violations and put on a long-running trial for the murder of an anti-fascist activist. Furthermore, other extreme rightwing politicians -no Golden Dawn members- who used to generate an explicit anti-semitic discourse during the crisis, are now members of the center-right government, and thus actively involved in the country's relations with Israel (e.g. the trilateral cooperation among Israel, Greece and Cyprus to build a natural gas subsea pipeline).

The decreased rate of the verbal attacks against ALBANIANS can be possibly examined in relation to the increased one against PAKISTANI; the third generation of ALBANIANS that came in Greece during the first migration flow is more or less integrated in the Greek society, while many of them have started going back to Albania. On the other hand, the migration flow from Asia is more recent. In addition, the term PAKISTANI, and especially its derogatory morphological variations, seems to be used as a generic term framing migrants that came to Greece from other Asian countries as well (e.g. Afghanistan, Bangladesh, Iraq) and not only from Pakistan.

The increased rate of the attacks against IMMIGRANTS can be possibly attributed to the ongoing refugee crisis and mainly to the fact that the effect of this crisis has started to be tangible in the Greek society, especially at the severely overcrowded camps on the islands (e.g. Moria in Lesvos). As for the REFUGEES, the results confirm again that it is more likely to verbally attack groups of people framed as IMMIGRANTS rather than as REFUGEES.

4.2 Main Types of Verbal Attacks

Fig. 7 illustrates the VAM1A/B rates for the five mostly attacked TGs for both periods enabling a direct comparison between them. As it is indicated by the share of the VAM1B rates, in 2019 IMMIGRANTS receive more attacks of this type than PAKISTANI as compared to the period 2013-2016, but still these two TGs constitute the main recipients of obscene messages in both periods. The rearrangement of the main targets of the attacks described in the previous section is reflected in the share of the VAM1A rates; the TGs who are mostly attacked with messages negatively evaluating specific attributes of them in 2019 appear to be MUSLIMS/ISLAM and PAKISTANI, and not JEWS and ALBANIANS as in 2013-2016.

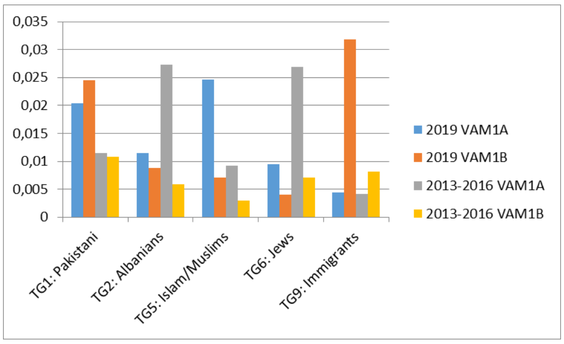

Figure 7: VAM1A/B rates per TG and time period.

JEWS may not constitute the main target of formal evaluations expressed in Twitter after the crisis, however, as it is illustrated in Fig. 8, they remain the main recipients of VAM2 messages and especially of calls for physical distinction; taking also into account that there is not a significant number of JEWS living in Greece as compared to the population of other groups in Greece (PAKISTANI, ALBANIANS, IMMIGRANTS), anti-semitism seems to still constitute a core component of the Greek xenophobia in the post crisis era. Another interesting finding is the increase of the VAM2 messages, in particular of the calls for ouster/deportation, against MUSLIMS/ISLAM; taking also into account the respective increase of such calls against PAKISTANI and IMMIGRANTS, this finding could indicate a possible interconnection between these three TGs.

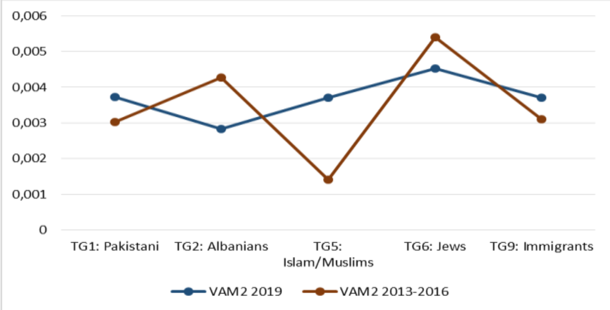

Figure 8: VAM2 rates per TG and time period.

4.3 Stereotypes and Prejudices

The qualitative analysis of the content of the attacks provides interesting insights regarding the dominant stereotypes and prejudices about the TGs under study also in the post crisis era. In the case of JEWS, the verbal attacks against them still entail a perception of a particular enmity towards the Greek nation and notions of hate-speech; the main terms in the construction of their image remain *εχθρότητα* (hostility) and *σαπούνι* (soap). However, as it is indicated in Fig. 9, the decrease of the rate of the attacks against them in 2019 is reflected also in the summary of the unique aggressive terms used to frame them as compared to the respective one in 2013-2016 (Fig. 4). Another interesting observation is the weakening of the "avarice" stereotype, which is a deep-rooted perception about JEWS in Greek society. Along with the financial crisis also the blame attribution patterns are also gone, while Greece and banks are no longer tagged as owned by Jews. The absence of the blame attribution patterns about the Greek crisis is observed also in the attacks against GERMANS.

Figure 9: Word Cloud of unique aggressive terms for JEWS.

In the case of ALBANIANS and PAKISTANI, the content of the verbal attacks captured against them in 2019 does not portray any major differences as compared to the attacks against them in the period 2013-2016; with the exception of a relative weakening of the criminality stereotype for ALBANIANS, they both keep being framed as inferior beings mainly through derogatory morphological variations of their nationality name (*Αλβανά*, *Πακιστανά*). No major differences arise also in the case of

MUSLIMS/ISLAM; the stereotypes that are derived by the semantics of the unique aggressive terms for the particular TG in 2019 are the same as in 2013-2016 (i.e. fanaticism, cultural inferiority, brutal violence, sexism, and irrationalism). As for IMMIGRANTS, the most frequent terms used to frame them in both time periods are the words *λαθρομετανάστες* (illegal immigrants) and *λάθρο* (slang term for illegal). Given the generic nature of this TG, in that they do not constitute specific ethnic group with individual characteristics, no unique aggressive terms about them were found. In both periods they are generally evaluated as inferior beings mainly in terms of cultural inferiority, criminality, and poor personal hygiene.

5. Discussion

We presented a replication of the VA analysis framework that was designed in the context of the XENO@GR project aiming to examine VA as an indicator of xenophobic attitudes in Twitter during the financial crisis in Greece, in particular during 2013-2016. The research goal of this paper was to re-examine VA as an indicator of xenophobic attitudes in Greek Twitter three years later, in the post crisis era, using the same NLP pipeline and lexical resources on a new dataset. The aim was to trace possible changes regarding the main targets, the types and the content of the verbal attacks against the same TGs, given also the ongoing refugee crisis and the political landscape in Greece as it was shaped after the elections in 2019. The results indicate an interesting rearrangement of the main targets of the verbal attacks; the two mostly attacked TGs during 2013-2016 (JEWS and ALBANIANS) are shifted to the 5th and 4th place, respectively, while PAKISTANI, IMMIGRANTS and MUSLIMS/ISLAM appear to be the top three attacked TGs in 2019.

The subsidence of the verbal attacks against JEWS seems to be in accordance with the remission of the financial crisis as well as with the switchover of the political landscape in Greece in 2019; verbal attacks against them are fewer and do not convey blaming for the crisis as in the period 2013-2016. Anti-semitic discourse in Greece has lost its main representative, the neo-Nazi party Golden Dawn. However, the types and the content of the attacks once again indicate anti-semitism as a core component of the Greek xenophobia confirming the existence of dominant perceptions that are deeply rooted in the Greek society and keep being reproduced after the financial crisis.

The increased rate of the verbal attacks against IMMIGRANTS seems to coincide with the ongoing refugee crisis; as a main entry point for asylum seekers and migration in Europe, Greece is still struggling to cope with the migration flows, while the effect of this crisis is now tangible, especially at the severely overcrowded camps on the islands. The types and the content of the attacks against them indicate that IMMIGRANTS are mainly framed as illegal, inferior and unwelcome, as in the period 2013-2016.

In the case of MUSLIMS/ISLAM, the results indicate an increase of islamophobia notions as compared to the period 2013-2016; the stereotypes that are derived by the semantics of the unique aggressive terms for the particular TG in 2019 are the same as in 2013-2016. However, the increase of the calls for deportation of MUSLIMS/ISLAM in 2019, taking also into account the respective increase of such calls against PAKISTANI and IMMIGRANTS, may indicate a qualitative difference as compared to 2013-2016, when the verbal attacks against MUSLIMS/ISLAM were mostly triggered by geopolitical events such as the rise of ISIS; this finding could indicate a possible interconnection between these three TGs and remains an open question for future research.

ALBANIANS and PAKISTANI constitute the largest immigrant populations in Greece. ALBANIANS are perhaps the most established group of foreigners in Greek public discourse, since the first wave of migration flow (early 1990s-mid 1990s). Almost thirty years later, and although they are more or less integrated in the Greek society, while many of them have started going back to Albania, they still are a main target of xenophobic attitudes. On the other hand, the migration flow from Asia is more recent. In addition, the content of the verbal attacks suggests that the term PAKISTANI -especially its derogatory morphological variations - seems to be used as a generic term framing migrants from other Asian countries as well (e.g. Afghanistan, Bangladesh, Iraq) and not only from Pakistan. A possible reconstruction of the image of foreigner in Greece that seems to be indicated by these findings remains an open question for future research.

6. Limitations and Contribution

Xenophobia is a complex social phenomenon that reflects a deeply rooted form of fear and hostility towards the “other”, who is perceived as a stranger to the group oneself belongs to. In the work presented in this paper, the notion of “other” is restricted to ten predefined TGs of interest based on specific criteria. Xenophobia is examined as a violent practice in terms of VA that constitutes only one aspect of xenophobic attitudes. Hence, the findings of this work provide insights in the context of a specific case study and not for the phenomenon of xenophobia in Greece in general. Furthermore, the findings result from Social Media data, in particular from a single platform study (snapshots of the Greek Twitter), hence they are not representative of the demographics and the attitudes of the general population in Greece.

In this setting, the work presented in this paper constitutes an example of how a language technology-based method can serve as a complementary research instrument in the context of Social Sciences and Humanities. Taking a step further from typical computational approaches, this work linked the results (the output of the method) to specific RQs including the critical step of their interpretation and presented an interdisciplinary end-to-end approach. The VA analysis framework was designed to provide both quantitative and qualitative information about the verbal attacks, helping to study the formulation of VA in relation to specific TGs, and to measure and monitor different aspects of VA as an important component of the manifestations of xenophobia in Greek Twitter.

The proposed framework can be extended to other targets (e.g. homophobic cyber-attacks) as well as to other languages, enabling cross-country studies and cross-cultural comparisons. Furthermore, given the high correlation between verbal and physical aggression (Hamilton and Hample, 2011) -in that VA may escalate to physical violence-, and the fact that physical and verbal attacks in the context of the XENO@GR project seem to be addressed to the same targets (Pontiki, Papanikolaou, and Papageorgiou, 2018), the proposed framework could provide valuable insights not only to political and social scientists but also to other stakeholders (e.g. policy makers).

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8. References

Antoniou, G., Dinas, E., Kosmidis, S. and Saltiel, L. (2014). *Antisemitism in Greece: Evidence from a Representative Survey*.

Bronwyn, H. (2002). A new pathology for a new South Africa? In D. Hook and G. Eagle (Eds), *Psychopathology and Social Prejudice* (pp. 169–184), Cape Town: University of Cape Town Press.

Delanty, G. and OMahony, P. (2002). *Nationalism and social theory: Modernity and recalcitrance of the Nation*. London: Sage.

Georgiadou, V. (2015). *Antisemitism in Greece: Concerns and considerations*. In: Antisemitism in Greece. Athens: British Embassy.

Hamilton, M. and Hample, D. (2011). Testing Hierarchical Models of Argumentativeness and Verbal Aggressiveness. *Communication Methods and Measures*, 5(3), pp. 250–273.

Kwok, I. and Wang, Y. (2013). Locate the hate: Detecting tweets against blacks. In: *Proceedings of the 27th AAAI Conference on Artificial Intelligence (AAAI 2013)*, Bellevue, Washington, 14-18 July, 2013, pp. 1621–1622.

Lialiouti, Z. and Bithymitris, G. (2013). The Nazis Strike Again': the concept of 'the German Enemy', party strategies and mass perceptions through the prism of the Greek economic crisis. In Karner, C. and Mertens, B. (Eds.) *The Use and Abuse of Memory: Interpreting World War II in Contemporary European Politics* (pp. 155–172). New Brunswick & London: Transaction Publishers.

Master, S. D. and Roy, M. K. (2000). Xenophobia and the European Union. *Comparative Politics*, 32 (4), pp. 419–436.

Papageorgiou, H., Prokopidis, P., Demiros, I., Giouli, V., Konstantinidis, A., and Piperidis S. (2002). Multi–level XML–based Corpus Annotation. In: *Proceedings of the 3rd International Conference on Language Resources and Evaluation (LREC 2002)*, Las Palmas, Spain, pp. 1723–1728.

Piperidis, S., Labropoulou, P. and Gavrilidou, M. (2017). clarin:el: a language resources documentation, sharing and processing infrastructure [in Greek]. In Georgakopoulos, T., Pavlidou, T.-S.,Pehlivanos, M. et al (eds), Proceedings of the 12th International Conference on Greek Linguistics, pp. 851–869. Berlin: Edition Romiosini/CeMoG.

Pontiki, M. (2019). Fine-grained Sentiment Analysis. PhD Thesis. University of Crete. [Online] Available at: http://thesis.ekt.gr/thesisBookReader/id/46115#page/1/mode/2up

Pontiki, M., Papanikolaou, K. and Papageorgiou, H. (2018). Exploring the Predominant Targets of Xenophobia-motivated behavior: A longitudinal study for Greece. In: *Proceedings of the 11th International Conference on Language Resources and Evaluation (LREC 2018), Natural Language Meets Journalism Workshop III*, Miyazaki, Japan, pp. 11 –15.

Prokopidis, P., Georgantopoulos, B., and Papageorgiou, H. (2011). A suite of NLP tools for Greek. In: *Proceedings of the 10th International Conference of Greek Linguistics*, Komotini, Greece, pp. 373–383.

Reynolds, V. and Vine, I. (1987). *The sociobiology of ethnocentrism: Evolutionary dimensions of xenophobia, discrimination, racism and nationalism*. London: Croom Helm.

Rösner, L., and Krämer, N. C. (2016). Verbal Venting in the Social Web: Effects of Anonymity and Group Norms on Aggressive Language Use in Online Comments. *Social Media & Society*, 2(3), pp. 69–94.

Sanguinetti, M., Poletto, F., Bosco, C., Patti, V. and Stranisci, M. (2018). An Italian Twitter Corpus of Hate Speech against Immigrants. In: *Proceedings of the 11th International Conference on Language Resources and Evaluation (LREC-2018)*, Miyazaki, Japan, pp. 2798–2805.

Strötgen, J. and Gertz, M. (2012). Temporal tagging on different domains: Challenges, strategies, and gold standards. In Calzolari et al. (eds), Proceedings of the 8th International Conference on Language Resources and Evaluation (LREC'12), pp. 3746–3753, Istanbul, Turkey.

Veer, K. V., Ommundsen, R., Yakushko, O., Higler, L., Woelders, S. and Hagen, K. A. (2013). Psychometrically and qualitatively validating a cross-national cumulative measure of fear-based xenophobia. *Quality & Quantity*, 47(3), pp. 1429–1444.

Voulgaris, Y., Dodos, D., Kafetzis, P., Lyrintzis, C., Michalopoulou, K., Nikolakopoulos, E. and Tsoukalas, K. (1995). Perceiving and dealing with the Other in present day Greece. *Elliniki Epitheorissi Politikis Epistimis*, 5, pp. 81–100.

Warner, W and Hirschberg, J. (2012). Detecting hate speech on the World Wide Web. In: *Proceedings of the 2012 Workshop on Language in Social Media (LSM 2012)*, Montreal, Canada, 7 June, 2012, pp. 19–26.

Waseem, Z. and Hovy, D. (2016). Hateful Symbols or Hateful People? Predictive Features for Hate Speech Detection on Twitter. In: *Proceedings of the NAACL 2016 Student Research Workshop*, San Diego, California, 13-15 June, 2016, pp. 88–93.